Gas Price Caps and Volatility Transmission in Commodity and Equity Markets

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Abstract

We study the impact of price cap mechanisms in the Natural Gas Title Transfer Facility on the commodity and equity markets. Our key findings are as follows: (i) a cap rule based on fixed price mechanism lowers the price consistently in most of the markets with no effect on volatility, thus acting as a possible short-run policy measure; (ii) the gas price cap mechanism adopted by the European Commission and currently in force seems to play a minor role in containing potential price spikes and has no significant impact in mitigating price volatility; (iii) a mechanism directly linked to the gas price volatility seems to perform better in containing gas prices and taming volatility spillover effects in commodity and equity markets. Our approach provides a way to assess ex-ante the market impacts of alternative policy interventions.

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Keywords: Gas Price, Price-cap mechanism, Volatility spillover, Commodity prices, Equity markets.

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1 Introduction

The price cap mechanism has come under the spotlight in the 2022 EU-Russia gas market turmoil reigniting the debate on the best price mitigation measure, while maintaining high domestic welfare. Much of the literature to date is concerned with industrial organization economics, specifically on how to reduce the monopolist's market power and increase domestic welfare when foreign monopolists operate within domestic markets. On the EU-Russia gas market, Ehrhart et al. (2023) prove that price caps Pareto-dominates the tariff, yielding higher domestic welfare and higher foreign monopoly profits. This is in line with various papers confirming the price cap as the best policy measure compared to tariffs or subsidies (e.g., De Meza (1979); Tower (1983); Kowalczyk (1994)). Other studies explored the effectiveness of the price caps by comparing the equilibrium points before and after the caps (e.g., Vossler et al. (2009); Reynolds and Rietzke (2018)). Still others explored conditional dependence between stock markets, commodity futures and prices in a univariate, multivariate, Value-at-Risk and portfolio optimization contexts using ARMA, GARCH, Extreme Value Theory, and copulae (e.g., Hussain and Li (2018), Marimoutou et al. (2009), Ohashi and Okimoto (2016), and Ghorbel and Trabelsi (2014)).

Focusing on the recent EU-Russia gas market turmoil, we complement this literature by exploring the price and volatility impacts on the commodity and stock markets induced by alternative price cap mechanisms in the Natural Gas Title Transfer Facility market.

Efficiently modeling commodity dynamics is particularly challenging due to the complex interplay between product trading and supply-demand imbalances resulting from economic conditions (Giot and Laurent (2003)). Moreover, the commodity market has been increasingly characterized by a financialization process (Cheng and Xiong, 2014): commodity derivatives and replicating financial securities became popular assets within investment portfolios, with scant or no positions on the underlying physical assets. As a result, commodity price dynamics have been extremely sensitive to financial market dynamics, business cycles, political and climate risk factors, thereby exhibiting large price fluctuations. The 2007-2008 Financial Crisis, when the Producer Price Index of All Commodities exhibited a year-on-year increase of 17.36% on July 2008 followed by a drop of 16.05% in July 2009[1], as well as the recent COVID-19 pandemic and the Russian-

[1] U.S. Bureau of Labor Statistics, Producer Price Index by Commodity: All Commodities [PPIACO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PPIACO,

Ukrainian conflict, highlight the fundamental importance to better inspect how commodity prices move and co-move over time, especially during extreme, systemic events, and which are the most efficient price mitigation measures that policymakers could implement.

We inspect the Title Transfer Facility (TTF) front-month price and investigate the effects of different price cap mechanisms on price and volatility dynamics for major international commodity and equity indices. Over the period from January 2013 to October 2023 we analyze the interconnections between European natural gas, commodities, global and local equity indices, also assessing the mitigation effects on price and volatility.

We adopt a univariate time-series approach to model the conditional mean and volatility of asset returns, next implementing two multivariate simulation approaches, Filtered Historical Simulations with block bootstrap (referred to as FHS), and conditional Extreme Value Theory (referred to as EVT) with copulae. FHS method was firstly introduced in Barone-Adesi et al. (1998) to compute portfolio risk measures and accounts implicitly for the interdependency across assets, which cannot be modeled efficiently by alternative methods as argued in Barone-Adesi et al. (2018). And indeed, through the FHS we are able to model and forecast the conditional price and volatility dependence structure of natural gas, commodity and equity market indices together without making explicit assumptions on the underlying causal mechanisms.

We compare three distinct price cap mechanisms (scenarios) for the TTF gas market and contrast them with a no-price intervention baseline. These scenarios include Fixed, Institutional, and Dynamic Price Caps. The Fixed Price Cap Scenario assumes a fixed price as the upper limit of TTF throughout the entire forecasting window. The Institutional Price Cap Scenario mirrors the current price cap mechanism introduced by the European Commission on February 15th, 2023. The Dynamic Price Cap Scenario imposes a limit on the volatility of the gas price rather than the price level itself; this is an alternative dynamic price cap mechanism to the Institutional one, we propose to better monitor surges in price volatility and connected market instabilities.

Our study reveals that the Fixed Price Cap exerts the highest price impact on all commodity asset classes, with substantial price reduction compared to no-price cap baseline and alternative cap mechanisms. Our Dynamic Price Cap mechanism has a strong price impact alike, being significantly higher than no-price cap and the Institutional mechanism,

November 10, 2022)

this one showing the lower, but still significant, price impact.

Only our Dynamical Price Cap exerts significant impact on volatility. We estimate a significant expected lowering of volatility relative to all cap alternatives and baseline scenario. While a Dynamic Price Cap consistently reduces the volatility compared with Institutional and baseline, when confronting with Fixed Price Cap, the volatility impact on agriculture and metal commodities is quite the same.

Price cap mechanisms have substantial impacts on equity markets. The Fixed Price Cap consistently reduces returns for some equity indices (*UK*, *France*, *Italy*, *Canada*, *Europe*, and *Spain* indices) and increases volatility for others (*Italy*, *Russia*, *Canada*, and *Spain*). Instead, the Dynamic Price Cap has a smaller impact on returns (none on *Europe* index), however significantly reducing market volatility for many indices (*Global*, *USA*, *China*, *Germany*, *UK*, *France*, *Russia*, *Canada*, and *Europe* indices).

All price cap mechanisms are expected to have a negative impact on equity markets returns compared to a scenario without a price cap mechanism. The most significant negative impact is with the Fixed Price mechanism, showing an expected annual cumulative return -3.15% (with FHS-based simulations) less than the baseline. On the other hand, the European cap mechanism currently in force exhibits a less severe negative impact, with a difference from the baseline of -0.42% (with FHS-based simulations). This is because such a price cap is less pervasive – we estimate a probability to activate the mechanism around 14 per cent –, and quite close to a world with no price cap.

These results have an important policy message, as they suggest that Fixed Price Cap mechanism could be planned as a extraordinary policy measure, to take in extreme crisis scenarios, while the Dynamic Price Cap, having an impact on both volatility and price, could be used within a long-run strategy to make more sustainable the energy market and to contain its inefficiencies. Interestingly, the gas price cap mechanism adopted by the European Commission and currently in force seems to play a minor role in containing potential price spikes also having virtually no impact in mitigating price volatility. A mechanism directly linked to the gas price volatility, as the one we propose in this paper, seems to play a better job in containing gas prices and taming volatility spillover effects in commodity and equity markets.

This paper is organized as follows: Section 2 we introduce the institutional background. Section 3 describes the cap scenarios, while Section 4 introduces the methodology. Data description is in Section 5, and the results and their discussion are in Section 6. Finally, Section 7 presents the conclusions.

2 Institutional Background

The Title Transfer Facility (TTF) is a virtual platform for natural gas in the Netherlands, which serves as the main benchmark to define the price of gas. The TTF has gained global attention after Russia cut gas deliveries to Europe following its invasion of Ukraine leading gas prices to hit record levels. According to the European Commission, the TTF was "*no longer an adequate reflection of market realities as it is unduly influenced by pipeline infrastructure bottlenecks in North-Western Europe and therefore Russian manipulation of natural gas supplies to the EU*"[2]. The European Commission, in response to the recognized need for intervention, launched an in-depth examination of potential price cap mechanisms, considering both fixed and dynamic price caps. Such an evaluation was aimed at proactively addressing and averting potential distortions within energy markets.

The European Commission, addressing the ongoing energy price crisis, proposed a set of emergency measures on October 18th, 2022. However, these measures did not include an immediate cap on gas prices, as many EU member states didn't all agree on this issue. Instead, the Commission sought approval from EU member states to draft a proposal for a temporary "maximum dynamic price" on trades at the Title Transfer Facility Dutch gas hub, which serves as a benchmark for European gas trading. Described as a "last-resort measure", this price limit proposal must meet specific conditions, including ensuring it does not lead to an increase in Europe's gas demand.

On December 20th, 2022 the European Union unveiled a proposed regulation introducing a gas price cap for the Title Transfer Facility. This regulation also offers comprehensive insights into the methodology for calculating the reference price of Liquefied Natural Gas (LNG) crucial to the mechanism. The cap mechanism was designed to be temporary: it is effective from February 15th, 2023, with a duration of one year. The proposed regulation underscores the pivotal role played by the TTF hub, accounting for approximately 80% of gas trading within the EU and the UK in the initial eight months of 2022. Notably, the

[2] European Commission, Questions and Answers on proposals to fight high energy prices and ensure security of supply, https://ec.europa.eu/commission/presscorner/detail/en/qanda_22_6226, 18 October 2022, Strasbourg.

TTF month-ahead settlement price for derivatives stands as the predominant benchmark in EU gas supply contracts.

The "Institutional Price Cap" is automatically triggered if the following market correction event occurs:

- the month-ahead price on the Title Transfer Facility exceeds 180 EUR/MWh (191.11 USD/MWh) for three working days;
- the month-ahead price on the Title Transfer Facility is 35 EUR higher than a reference price for LNG on global markets for the same three working days.

The mechanism prescribes that gas transactions above the "dynamic bidding limit" are not allowed to take place. The proposed regulation additionally provides elucidation on the methodology for ascertaining the LNG reference price. It emphasizes the use of suitable benchmarks to establish a reference price that accurately mirrors the prevailing global trends in LNG prices.

On December 30th, 2022, Council Regulation (EU) 2022/2576, titled "Enhancing solidarity through improved coordination of gas procurement, reliable pricing benchmarks, and cross-border gas exchanges," came into effect. This regulation mandates the Agency for the Cooperation of Energy Regulators (ACER) to undertake the following responsibilities: commence the publication of a fresh daily assessment for LNG prices no later than January 13rd, 2023; establish a daily LNG benchmark starting from March 31st, 2023. Furthermore, the Regulation confers upon ACER the requisite authority to gather essential data required for the formulation of the LNG benchmark. This benchmark aims to enhance market transparency through compulsory data reporting, offering a reflection of real-world LNG prices.

3 Gas Price Scenarios

To explore price and volatility transmission effects induced by different policy interventions, we consider four scenarios depending on the cap mechanism we impose on the TTF month-ahead gas price path: (i) the Baseline Scenario (BS), (ii) the Fixed Price Cap Scenario (FS), (iii) the Institutional Price Cap Scenario (IS) and (iv) the Dynamic Price Cap Scenario (DS). To formalize our methodological approach, we first present our econometric framework and next define each scenario.

3.1 Econometric Framewok

We consider N assets and assume that their prices are observed in T consecutive (daily) realizations. For each $i = 1, \dots, N$ and $t = 1, \dots, T$, we denote with P_t^i the price of asset i at time t. Letting $r_t^i = \ln\left(P_t^i / P_{t-1}^i\right)$ be the logarithmic return of asset i at time t and σ_t^i its conditional volatility, the TTF month-ahead price follows the Itô stochastic process:

$$\frac{dP_t^{TTF}}{P_t^{TTF}} = r_t^{TTF} dt + \sigma_t^{TTF} d\hat{W}_t^{TTF}, \tag{1}$$

where $\frac{dP_t^{TTF}}{P_t^{TTF}}$ is the price change in TTF at time t; r_t^{TTF} is the drift of TTF's returns at time t; σ_t^{TTF} is the conditional volatility of the TTF at time t; $\hat{W}_t^{TTF}$ is the Wiener process at time t, denoting the stochastic noise (random shock) affecting the returns of TTF.

The same process is assumed for the generic asset's i returns:

$$\frac{dP_t^i}{P_t^i} = r_t^i dt + \sigma_t^i d\hat{W}_t^i, \tag{2}$$

where r_t^i is the drift of asset's i returns at time t; σ_t^i is the conditional volatility of asset's i at time t; $\hat{W}_t^i$ is the Wiener process at time t for asset i. Hence, the correlation between asset i and TTF shocks ρ^i is as follows:

$$\mathbb{E}\left[d\hat{W}_t^i d\hat{W}_t^{TTF}\right] = \rho^i dt. \tag{3}$$

Equations (1) and (2) can be expressed (through Cholesky factorization) in terms of independent Wiener processes, thereby relating asset price dynamics with TTF shocks:

$$\begin{cases} \frac{dP_t^{TTF}}{P_t^{TTF}} & = r_t^{TTF} dt + \sigma_t^{TTF} dW_t^{TTF}, \\ \frac{dP_t^i}{P_t^i} & = r_t^i dt + \sqrt{1-\rho^{i2}} \sigma_t^i dW_t^i + \rho^i \sigma_t^i dW_t^{TTF}, \end{cases} \tag{4}$$

where $\sqrt{1-\rho^{i2}}\sigma_t^i dW_t^i$ is the stochastic component of the price change for asset i. Specifically: $\sqrt{1-\rho^{i2}}$ is a scaling factor that adjusts the volatility σ_t^i of asset i based on the correlation coefficient ρ^i. It accounts for the portion of asset i's volatility that is not correlated with the TTF; dW_t^i is the Wiener process differential for asset i, which is independent from the TTF shocks.

At this point, we can discretize Equation (2) as follows:

$$P_{t+dt}^i = P_t^i + P_t^i r_t^i dt + P_t^i \sigma_t^i z_t^i, \tag{5}$$

with $\hat{W}^i_{t+dt} - \hat{W}^i_t = z^i_t$. Innovations in asset price i are assumed to follow an iid distribution, namely $\mathbb{E}\left[z^i_t\right] = 0$ and $\mathbb{V}\left[z^i_t\right] = 1$, with $\{z^i_t\}^{i=1,\dots,N}_{t=1,\dots,T}$ denoting a sequence of standardized innovations for asset price i.

3.1.1 Price Dynamics Modeling

To estimate the conditional mean, r^i_t, and conditional volatility, σ^i_t, for asset dynamics, we rely on different GARCH specifications proposed in past studies to inspect the aggregate relationships between macroeconomic factors and stock and bond returns (eg., Flannery and Protopapadakis (2002), Jones et al. (1998), Brenner et al. (2009)). Specifically, we consider three conditional models[3]:

1. the ARMA(1,1)-GARCH(1,1) (Bollerslev (1986)), which combines an autoregressive moving average (ARMA) process for the mean with a generalized autoregressive conditional heteroskedasticity (GARCH) process for the variance:

$$\begin{aligned} r_t &= \phi_0 + \phi_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t, \\ \varepsilon_t &= \sigma_t z_t, \\ \sigma_t^2 &= \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2. \end{aligned} \tag{6}$$

   As known, the ARMA(1,1) process has three parameters: ϕ_0 is the constant mean of returns, while ϕ_1 and θ_1 are the autoregressive and moving average coefficients, respectively. The condition $|\phi_1| < 1$ must hold for stationarity. The GARCH(1,1) process has three parameters: $\omega > 0$, $\alpha_1 > 0$, and $\beta_1 > 0$, corresponding to the constant, the weight of past squared innovations (ARCH component coefficient), and the weight of past conditional variances (GARCH component coefficient), respectively. To preserve stationarity, we need to impose the condition $\alpha_1 + \beta_1 < 1$.

2. The ARMA(1,1)-EGARCH(1,1) (Nelson (1991)), which combines an ARMA process for the mean with an exponential form for the variance equation to ensure non-negative values. The model allows for asymmetric volatility responses to positive and negative shocks by introducing a logarithmic transformation of the variance

[3]To simplify the notations, we remove the superscript i then using r_t instead of r^i_t.

process and an additional parameter capturing the impact of negative shocks:

$$\begin{aligned}
r_t &= \phi_0 + \phi_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t, \\
\varepsilon_t &= \sigma_t z_t, \\
\ln(\sigma_t^2) &= \omega + \alpha_1 \left[|z_{t-1}| - \mathbb{E}\left[|z_{t-1}|\right]\right] + \beta_1 \ln(\sigma_{t-1}^2) + \xi_1 z_{t-1}.
\end{aligned} \tag{7}$$

This model has the same autoregressive and moving average parameters together with the same constraints as ARMA(1,1)-GARCH(1,1). The EGARCH(1,1) process has four parameters: ω, α_1, β_1, and ξ_1, which are the constant, the weight of past squared standardized innovations (ARCH component coefficient), the weight of past conditional variances (GARCH component coefficient) on the logarithmic scale, and the impact of past negative shocks (leverage component coefficient), respectively.

3. The ARMA(1,1)-GJR(1,1) (Glosten et al. (1993)), which is an extension of the GARCH model that allows for an asymmetric response of the variance to positive and negative shocks. As discussed in Engle and Ng (1993) and Rosenberg and Engle (2002), GJR GARCH model provides more flexibility in capturing the leverage effect and describes the data best. Computationally, the model introduces an additional parameter capturing the impact of negative shocks on the conditional variance:

$$\begin{aligned}
r_t &= \phi_0 + \phi_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t, \\
\varepsilon_t &= \sigma_t z_t, \\
\sigma_t^2 &= \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, + \gamma_1 \mathbb{I}_{\{\varepsilon_{t-1} < 0\}} \varepsilon_{t-1}^2.
\end{aligned} \tag{8}$$

As for ARMA(1,1)-GARCH(1,1), this model has the same contraints as well as the same autoregressive and moving average parameters. The GJR(1,1) process has four parameters: $\omega > 0$, $\alpha_1 > 0$, $\beta_1 > 0$, and $\gamma_1 \in \mathbb{R}$, corresponding to the constant, the weight of past squared innovations (ARCH component coefficient), the weight of past conditional variances (GARCH component coefficient), and the weight of past squared, negative innovations (leverage component coefficient), respectively. $\mathbb{I}$ is the indicator function which takes the value 1 if the condition $\varepsilon_{t-1} < 0$ is met. Imposing $\alpha_1 + \gamma_1 \geq 0$ and $\alpha_1 + \beta_1 + \gamma_1 < 1$ ensures the model to be stationary.

3.2 Scenarios

The conditional models for asset returns are used to inspect the price and volatility dynamics in the four scenarios over a pre-specified forecasting time window. We consider a forecasting time window of length H, and define P_h^i be the predicted daily price of asset $i = 1, \ldots, N$ at time $h = T+1, \ldots, T+H$. By denoting σ_h^i the predicted daily conditional volatility of asset i at time h, each scenario is formalized as described below.

3.2.1 Baseline Scenario

The Baseline Scenario (BS) serves as a benchmark to contrast with the other three scenarios. Here, no authority intervention or constraints are imposed on the predicted gas price. As a result, gas price varies over time without restrictions, while remaining in non-negative territory[4]:

$$BS = \{P_h^{TTF} | P_h^{TTF} \in [0, +\infty)\}_{h=T+1,\ldots,T+H}. \tag{9}$$

In the BS, the univariate expected value and corresponding conditional volatility of the returns for asset i at time T are:

$$\begin{cases} \mathbb{E}_T\left[P_h^i | BS\right] = \mathbb{E}_T\left[P_h^i\right], \\ \mathbb{E}_T\left[\sigma_h^i | BS\right] = \mathbb{E}_T\left[\sigma_h^i\right]. \end{cases} \tag{10}$$

3.2.2 Fixed Price Cap Scenario

The Fixed Price Cap Scenario (FS) introduces an upper limit, denoted by $\bar{P}^{TTF}$, on the daily TTF month-ahead gas price. This constraint ensures that the TTF gas price remains within the specified range throughout the forecasting time horizon:

$$FS = \{P_h^{TTF} | P_h^{TTF} \in \left[0, \bar{P}^{TTF}\right]\}_{h=T+1,\ldots,T+H}. \tag{11}$$

The Fixed Price Cap serves as a mechanism to control and limit the upward movement of the gas price. The upper bound on (predicted) TTF price, which serves to prevent potential excessive price spikes, is the first policy intervention option we consider. Being the benchmark to define the European price of gas, the TTF price plays a pivotal role also for other assets. Mathematically we have:

$$\{P_h^i | FS\} \qquad \forall h = T+1, \ldots, T+H \text{ and } i = 1, \ldots, N \tag{12}$$

[4]We excluded negative commodity prices being a case which is out the scope of this study.

with conditional volatility:

$$\{\sigma_h^i | FS\} \qquad \forall h = T+1, \ldots, T+H \text{ and } i = 1, \ldots, N. \tag{13}$$

3.2.3 Institutional Price Cap Scenario

The Institutional Price Cap Scenario (IS) replicates the regulatory price cap mechanism imposing a price ceiling of 180 EUR/MWh (191.11 USD/MWh) when two specific market events occur simultaneously: the TTF month-ahead price exceeds 180 EUR/MWh (191.11 USD/MWh) for three consecutive working days and the TTF month-ahead price is 35 EUR/MWh (37.16 USD/MWh) higher than a reference price for LNG in global markets during the same three consecutive working days. The Agency for the Cooperation of Energy Regulators (ACER) has been tasked on December 2022 with creating and publishing a new daily LNG price assessment (P^{LNG}), starting on 01/13/2023 (see section 2). Mathematically we have:

$$IS = \left\{ (P_h^{TTF}) \middle| \begin{array}{c} \prod_{i=1}^{3} \mathbb{I}_{\{P_{h-i+1}^{TTF} > 191.11\}} < 1 \\ \prod_{i=1}^{3} \mathbb{I}_{\{P_{h-i+1}^{TTF} > P_{h-i+1}^{LNG} + 37.16\}} < 1 \end{array} \right\} \qquad \forall h = T+3, \ldots, T+H. \tag{14}$$

where the indicator function $\mathbb{I}$ takes the value 1 whenever the TTF month-ahead price exceeds 191.11 USD/MWh for three working days *and* the TTF month-ahead price is 35 EUR = 37.16 USD higher than the reference price for P^{LNG} for the same three working days[5]. Gas price dynamics can then be formally expressed as:

$$\{P_h^i | IS\} \qquad \forall h = T+1, \ldots, T+H \text{ and } i = 1, \ldots, N \tag{15}$$

and conditional volatilities:

$$\{\sigma_h^i | IS\} \qquad \forall h = T+1, \ldots, T+H \text{ and } i = 1, \ldots, N. \tag{16}$$

3.2.4 Dynamic Price Cap Scenario

The Dynamic Price Cap (DS) is alternative to the Institutional Price Cap, and explores whether a mechanism connected to volatility dynamics instead of the price itself could be more efficient in taming the TTF price and volatility spikes.

[5]The gas price thresholds were converted in USD using the same exchange rate employed by the regulatory commission to convert 180 EUR to 191.11 USD.

The Dynamic Price Cap imposes a limit on the conditional expected volatility of the TTF month-ahead gas price through quantile-based stability criteria. Specifically, the mechanism requires the following rules be met:

1. the quartiles of forecasted TTF conditional volatility must not exceed the quartiles of historical conditional volatility;

2. the average forecasted TTF conditional volatility must not exceed the mean historical conditional volatility;

3. the TTF price at any point in the forecasting time window must be lower than the 99th percentile of historical prices.

More formally, by letting $q_j(\hat{\sigma}_t^{TTF})$ and $\bar{\hat{\sigma}}_t^{TTF}$ be the quartiles $j = 0, 0.25, 0.50, 0.75, 1$ and the average historical conditional volatility, respectively, and let $q_{0.99}(P_t^{TTF})$ be the 99th historical percentile of TTF month-ahead gas price, the Dynamic Price Cap Scenario can be defined as follows:

$$DS = \left\{ (P_h^{TTF}, \sigma_h^{TTF}) \left| \begin{array}{c} q_j(\sigma_h^{TTF}) \leq q_j(\hat{\sigma}_t^{TTF}) \\ \bar{\sigma}_h^{TTF} \leq \bar{\hat{\sigma}}_t^{TTF} \\ P_h^{TTF} \in \big[0, q_{0.99}(P_t^{TTF})\big) \end{array} \right. \right\} \quad \forall h = T{+}1, \ldots, T{+}H \text{ and } j = 0, 0.25, 0.50, 0.75, 1. \tag{17}$$

Gas price dynamics are then expressed as

$$\{P_h^i | DS\} \qquad \forall h = T + 1, \ldots, T + H \text{ and } i = 1, \ldots, N \tag{18}$$

with the conditional volatility:

$$\{\sigma_h^i | DS\} \qquad \forall h = T + 1, \ldots, T + H \text{ and } i = 1, \ldots, N. \tag{19}$$

Our Dynamic Price Cap is designed to take into account market expectations and the potential amplification effect resulting from the multiple interconnections among commodity and equity prices. By imposing historical data-driven constraints on expected conditional gas price volatility, the proposed mechanism provides a more effective mechanism for governing excessive gas price volatility and connected spillover effects on commodity and equity markets.

3.3 Comparative Analysis

Having specified the processes for prices and volatilities with (Fixed, Institutional and Dynamic) and without (Baseline) price cap mechanisms, we next examine the effects of the different price dynamics on other assets prices and volatilities under the three scenarios. Formally, we study the following relationship:

$$\begin{cases} \mathbb{E}_T\left[P_h^i|BS\right] \gtreqqless \mathbb{E}_T\left[P_h^i|FS\right] \gtreqqless \mathbb{E}_T\left[P_h^i|IS\right] \gtreqqless \mathbb{E}_T\left[P_h^i|DS\right] \\ \mathbb{E}_T\left[\sigma_h^i|BS\right] \gtreqqless \mathbb{E}_T\left[\sigma_h^i|FS\right] \gtreqqless \mathbb{E}_T\left[\sigma_h^i|IS\right] \gtreqqless \mathbb{E}_T\left[\sigma_h^i|DS\right]. \end{cases} . \tag{20}$$

By contrasting the three cap rules with the Baseline Scenario, we provide a *what-if analysis* for commodity and equity markets under different policy intervention options. The approach is particularly useful for regulators, as costs and benefits from specific policy interventions can be measured in terms of expected market price and volatility impacts. It is useful for investors alike, since the ex-ante estimation of mean and volatility are core ingredients in forming optimal investment portfolios, especially when we condition on extreme, and – as in our case – regulatory-based events.

4 Methodology

The methodology used in this paper includes the following steps: (i) estimation of ARMA-GARCH-type models, (ii) simulation through FHS following Barone-Adesi et al. (2018) with block bootstrap and EVT with copulae; (iii) scenario generation through 3-Dimensional matrices (3D) similarly to McNeil and Smith (2012); (iv) price-cap impact assessment through ANOVA test. The time window used for model estimation is from 10/07/2013 to 10/18/2022, when the European Commission announced the gas price cap mechanism. The period from 10/20/2022 to 10/20/2023 is used to run an out-of-sample analysis providing ex-ante estimation of the potential market impacts of the alternative price cap mechanisms.

4.1 Model Estimation

We first estimate the conditional models' parameters, as described in Section 3.1. The parameters in the mean return equation, the equation for the conditional standard deviation, and the probability distribution for return innovations are jointly estimated through

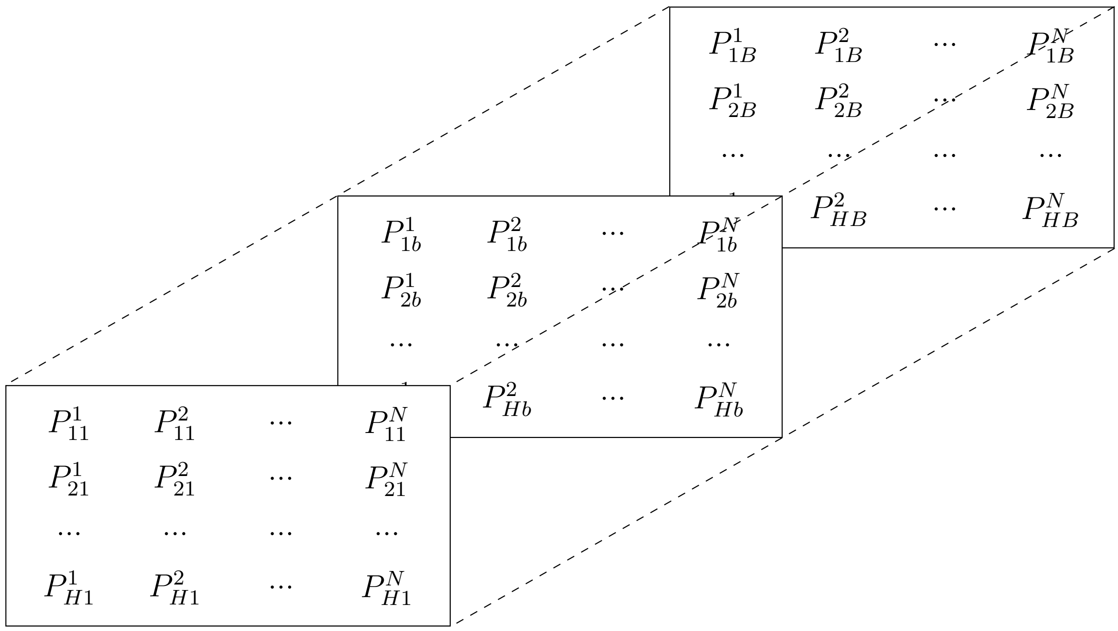
Maximum Likelihood. To account for the heavier tails often observed in commodity price data, we employ the Student-t to model innovation distribution. Specifically, we assume that standardized residuals $\{z_t^i\}_{t=1,\ldots,T}^{i=1,\ldots,N}$ are iid following a Student-t distribution with ν degrees of freedom. We preliminary checked the iid assumption by running standard diagnostic tests (specifically, we examined the standardized residuals and their squared values for each time series and model).

4.2 Scenario Simulations

After calibrating the parameters of the conditional models to account for the correlation between TTF month-ahead and other asset shocks (Equation (4)), we generate joint forecasts for each asset. We do this by relying on Multivariate FHS with block bootstrap and conditional EVT with copulae models[6]. The FHS and EVT methods enable us to generate $B^k = 5,000$ joint forecasts (states of the world) for each of the $k = [1, 2, 3]$ conditional model (section 3.1.1) over a forecasting time horizon of 250 days, then resulting in $B = 5,000 \times 3 = 15,000$ simulated states of the world using FHS and $B = 5,000 \times 3 = 15,000$ using EVT.

The $15,000$ states of the world generated with FHS and the $15,000$ states of the world generated with EVT are forming two 3D matrices (one for FHS and one for EVT), in which the first and the second dimension are the $H = 250$ (rows) days and N (columns) assets, respectively, while the third (pages) are the $B = 15,000$ simulated states of the world, given by the concatenation along the third dimension of the conditional models results. In graphic terms:

[6]Detailed explanations of FHS and conditional EVT with copulae models are in the Appendix.



At this point, the Fixed, the Institutional and Dynamic Price Cap scenarios are computed starting from the Baseline Scenario realizations:

$$FS = \{b = 1, \dots, B | P_{hb}^{TTF} \in \big[0, \bar{P}^{TTF}\big]\}, \tag{21}$$

$$IS = \left\{ b = 1, \dots, B \left| \begin{array}{r} \prod_{i=1}^{3} \mathbb{I}_{\{P^{TTF}_{h-i+1,b} > 191.11\}} < 1 \\ \prod_{i=1}^{3} \mathbb{I}_{\{P^{TTF}_{h-i+1,b} > P^{LNG}_{h-i+1,b} + 37.16\}} < 1 \end{array} \right. \right\}, \tag{22}$$

and

$$DS = \left\{ b = 1, \dots, B \left| \begin{array}{l} q_j(\sigma_{hb}^{TTF}) \leq q_j(\hat{\sigma}_t^{TTF}) \\ \quad \overline{\sigma}_{hb}^{TTF} \leq \overline{\hat{\sigma}}_t^{TTF} \\ \quad P_{hb}^{TTF} \in \big[0, q_{0.99}(P_t^{TTF})\big) \end{array} \right. \right\}, \tag{23}$$

where P_{hb}^{TTF} is the predicted daily price of gas at time h in the state of the world b. Similarly, σ_{hb}^{TTF} is the predicted daily conditional volatility of gas at time h in the state of the world b.

Price-cap simulations were run based as follows:

- In the Fixed Price Cap scenario, we set the upper limit of $\bar{P}^{TTF}$ at 113 USD/MWh (106.43 EUR/MWh), which is more conservative than actual price cap of 180 EUR/MWh (191.11 USD/MWh) agreed on December 2022, but in line with the price observed on 10/18/2022[7].

[7] At that time, market rumors placed the Fixed Price Cap between 111.48 USD/MWh (105 EUR/Mwh) and 122.10 USD/MWh (115 EUR/MWh).

- As discussed in Section 2, the Institutional Price Cap activates a price ceiling of 180 EUR/MWh (191.11 USD/MWh) when two specific market events occur simultaneously: the TTF month-ahead price exceeds 180 EUR/MWh (191.11 USD/MWh) for three consecutive working days and the TTF month-ahead price is 35 EUR/MWh (37.16 USD/MWh) higher than a reference price for LNG in global markets during the same three consecutive working days. The Agency for the Cooperation of Energy Regulators (ACER) has been tasked on December 2022 with creating and publishing a new daily LNG price assessment, starting on 01/13/2023. Moreover, ACER establishes a daily LNG benchmark since 05/31/2023. To cover the entire forecasting window $h \in [1, H]$ (October 2022-October 2023), we thus estimate the LNG benchmark for each state of the world $b \in [1, B]$ in retrospect by computing the following robust OLS regression[8]:

$$\begin{aligned}\widehat{P_h^{LNG}} &= \exp\left(1.0891^{***} + 0.3057^{***} \ln P_h^{TTFspot} + 0.3938^{***} \ln P_{h-1}^{TTFspot}\right), \\ R^2 &= 0.7853, \bar{R}^2 = 0.7817, \\ \text{Obs} &= 123, \text{RMSE} = 26.1364.\end{aligned} \tag{24}$$

Next, with the coefficients estimates, we projected the ex-ante LNG forecast as follows:

$$P_{hb}^{LNG} = \exp\left(1.0891 + 0.3057 \ln P_{hb}^{TTFspot} + 0.3938 \ln P_{h-1,b}^{TTFspot}\right). \tag{25}$$

- The price and volatility quartile constraints used by the Dynamic Price Cap (see section 3.2) were computed over the period from 2013 to 2019: we consider this as the reference period for TTF front-month stable volatility period (indeed, no systemic events occurred in this time interval). Moreover, by encompassing the entire time series, the $q_{0.99}(P_t^{TTF})$ value for the TTF front-month amounted to 207.88 USD/MWh.

4.3 Comparative Analysis

For each cap mechanism, and for each conditional model separately, we excluded states of the world (pages of the 3D matrices) from the set B if the predicted TTF front-month

[8] To identify the best model we employed a step-wise regression approach with robust inference techniques including wild bootstrap based on a Rademacher distribution and double bootstrap for the F-stat.

price (or volatility, when focusing on the Dynamic Price Cap scenario) in any of those states of the world did not comply with the cap mechanism under scrutiny[9]. Afterwards, we run a series of N-Way Analysis of Variance (ANOVA) tests to assess the statistical significance of the price cap mechanism impacts in terms of *price* and *volatility* differences. To that end, for each scenario and conditional model, we computed the cumulative price return, the mean and median (both annualized) conditional volatility over the forecasting time window:

$$\bar{r}^i_b = \sum_{h=1}^{H} r^i_{hb} \tag{26}$$

$$\bar{\sigma}^i_b = \left(\frac{1}{H} \sum_{h=1}^{H} \sigma^i_{hb} \right) \cdot \sqrt{H} \tag{27}$$

$$\tilde{\sigma}^i_b = \text{median}(\sigma^i_{1b}, \sigma^i_{2b}, \ldots, \sigma^i_{Hb}) \cdot \sqrt{H} \tag{28}$$

We performed a series of ANOVA tests to examine group differences and interactions by focusing on the following groupings:

- Scenario (BS, FS, IS, DS);
- Asset Class (Energy excluding TTF, Metals, Agriculture, Equity);
- Single Assets excluding TTF (54 assets in total);
- Method (FHS, EVT);
- Model (ARMA-GARCH, ARMA-EGARCH, ARMA-GJR).

This way allows us to assess the statistical significance of differences between scenarios, simulation methods, and conditional models, while aggregating the results at the asset class level. The rationale of the procedure is to compare the Baseline Scenario, in which no price cap is at play and therefore TTF prices are not upper bounded, with *constrained* scenarios, where price caps force TTF prices to remain under specific boundaries. Statistically significant differences in returns and/or volatility between Baseline vs. constrained scenarios reflect significant price cap impacts.

[9]In other words, if the TTF gas price in a specific state of the world b^* did not meet, for example, the requirements for the Fixed Price Cap rule, we excluded the realizations of that particular state of the world b^* for all the assets in the sample.

5 Data

The data used in our empirical analysis include commodity prices, commodity indices and equity indices, all collected on daily basis, over the period from 07/10/2013 (the earliest available date for the TTF front-month) to 10/18/2022. Analytically:

- Dutch TTF Gas Monthly Near Term (NDEX EUR/MWh) daily price in USD/MWh (data come from Factset) to proxy the TTF front-month price as defined by the European Commission on which the caps have been imposed;

- Natural Gas Spot EOD Price TTF (EEX EUR/mwh) daily price in USD/MWh (data come from Factset) to proxy the TTF spot price for estimating the LNG benchmark;

- S&P GSCI single-commodity spot indices[10] for the following commodities: *AllCrude*, *BrentCrudeOil*, *CrudeOil*, *Energy*, *Gasoil*, *HeatingOil*, *NaturalGas*, *Petroleum*, *UnleadedGasoline*, *AllMetals*, *Aluminum*, *Copper*, *Gold*, *IndustrialMetals*, *IronOre*, *Lead*, *Nickel*, *NorthAmericanCopper*, *Palladium*, *Platinum*, *PreciousMetals*, *Silver*, *Tin*, *Zinc*, *Agriculture*, *AgricultureLivestock*, *AllCattle*, *AllWheat*, *Cocoa*, *Coffee*, *Corn*, *Cotton*, *FeederCattle*, *Grains*, *KansasWheat*, *LiveCattle*, *Livestock*, *Softs*, *SoybeanOil*, *Soybeans*, *Wheat*;

- S&P BMI equity indices[11] for the following country or regions: *Canada*, *China*, *Europe*, *France*, *Germany*, *Global*, *India*, *Italy*, *Japan*, *Russia*, *Spain*, *UK*, *USA*.

Our intention was to select, firstly, those commodities that exhibited highest sensitivity towards Dutch TTF Gas Monthly Near Term and Natural Gas Spot EOD Price TTF on the onset of the Russian-Ukrainian, as identified by the World Bank[12]

Secondly, as documented in many papers, gas (e.g., Acaravci et al. (2012); Gatfaoui (2016); Geng et al. (2021)) and more generally commodity markets (e.g., Buyuksahin et al.

[10] S&P Standard and Poor's Goldman Sachs Commodity Indices, https://www.spglobal.com/spdji/en/index-family/commodities/.

[11] S&P Standard and Poor's Broad Market Indices, https://www.spglobal.com/spdji/en/index-family/equity/global-equity/sp-global-bmi/#indices.

[12] Word Bank Special Focus, *Pandemic, war, recession: Drivers of aluminum and copper prices*, Word Bank (2022b) and Word Bank Special Focus, *The Impact of the War in Ukraine on Commodity Markets*, Word Bank (2022a).

(2010); Creti et al. (2013); Delatte and Lopez (2013)), while appearing segmented from the stock markets, when considering returns, commodity volatility indicates a nontrivial degree of market integration with equities (Christoffersen et al. (2019)). We then explored major equity international indices, including the *Global* index, to proxy the worldwide equity portfolio, the *European* index, which is crucial to understand macro regional-based price dynamics, as well as single EU country equity indices (*Germany*, *UK*, *France*, *Italy*, and *Spain*) and non-EU countries (*USA*, *China*, *Japan*, *India*, and *Canada*). We also focus on the *Russian* equity index, which is important to assess the potential impact of the TTF gas price cap on the Russian market, given that Russia is a major supplier of gas to the TTF.

5.1 Parameter Estimates

5.1.1 Conditional Models

Figures 1 to 3 show parameter estimates for various conditional models across all assets.

In the ARMA(1,1)-GARCH(1,1) model, the constant mean (*Const1*) is statistically significant mainly for equity indices, while it is less significant for other assets. Other conditional models exhibit statistical significance for constant means in only a few assets.

By and large, we find a relatively small number of assets with statistically significant AR coefficients. Interestingly, these assets with significant AR coefficients have also significant MA coefficients in all models, indicating persistent auto-correlation effects.

The intercept in volatility equations (*Const2*) differs among models. In the ARMA(1,1)-GARCH(1,1) model, most assets show statistically significant constant conditional volatility, except for *Gold*, *IndustrialMetals*, and some others. In the ARMA(1,1)-EGARCH(1,1) model, the pattern is different, with only a few assets having non-significant constant conditional volatility.

The ARMA(1,1)-GJR(1,1) model aligns with the ARMA(1,1)-GARCH(1,1) model for assets with non-significant constant conditional volatility. The presence of significant ARCH and GARCH terms is substantial for both ARMA(1,1)-GARCH(1,1) and ARMA(1,1)-EGARCH(1,1) models, indicating that past conditional volatility strongly impacts future volatility. However, the ARMA(1,1)-GJR(1,1) model shows a different pattern, with GARCH terms being non-significant for most equity indices.

For ARMA(1,1)-EGARCH(1,1) and ARMA(1,1)-GJR(1,1) models, the leverage coefficient is statistically significant for about half of the commodities, suggesting their sensitivity to asymmetric volatility responses. Equity indices consistently show statistical significance for the leverage coefficient, indicating substantial asymmetric volatility responses to negative shocks.

The Degrees of Freedom parameter (DoF) is generally statistically significant, implying that the Student's t distribution accurately represents asset return distributions. However, *Softs* lacks statistical significance for the DoF parameter in the ARMA(1,1)-EGARCH(1,1) model.

5.1.2 Generalized Pareto Distribution

Figure 4 displays parameter estimates of the Generalized Pareto Distribution's (GPD) tails, representing both the left and right tails of the piece-wise cumulative distribution function. A detailed explanation of the GPD and of how its parameters have been estimated are in the Appendix.

The parameter u is the threshold (or starting point) of the GPD distribution, while T_u/T identifies the proportion of tail data, acting as a percentile threshold. We calculated the threshold parameters for both tails using the automated threshold selection method proposed by Bader et al. (2018), with a 5.00% significance level, which is more sophisticated than the conventional fixed percentile rule. Remarkably, for most assets in our sample, the data accommodated within the GPD tails exceeds the traditional 20% (left) and 80% (right) thresholds of the percentile rule, resulting in fatter tails and moving towards more extreme values.

Threshold estimates display minimal variability across conditional models, with some exceptions. For example, the lower tail of *PreciousMetals* appears thinner in the ARMA(1,1)-EGARCH(1,1) model, while the upper tail of *SoybeanOil* is slimmer in the ARMA(1,1)-EGARCH(1,1) model. The estimates for most assets in the ARMA(1,1)-GARCH(1,1) and ARMA(1,1)-GJR(1,1) models are similar, with lower threshold parameters averaging between the 20th and 30th percentiles and upper thresholds between the 60th and 80th percentiles. Equity indices exhibit thin lower tails and thick upper tails.

The shape parameter (ξ) in the Generalized Pareto Distribution (GPD) characterizes the probability of extreme events beyond the threshold. Positive values of ξ indicate heavy tails, then implying frequent extreme events. Negative ξ values suggest light tails with less frequent extreme events, while $\xi = 0$ results in an exponential distribution. Figure 4 shows ξ values within ± 0.2 for both tails. Notably, *TTFFut* has a right fat tail ($\xi \approx 0.2$), indicating a higher likelihood of extreme positive returns. Other assets with strong positive shape parameters include *Russia* (lower tail) and *Nickel*, *IronOre*, and *France* (upper tail).

The scale parameter (σ) of the GPD measures the magnitude of extreme events beyond the threshold. On average, it ranges from 0.6 to 0.8 in the lower tail and 0.4 to 0.8 in the right tail.

5.2 Summary Statistics

Table 1 provides a comprehensive overview of the summary statistics for returns and conditional volatilities (averages of the three conditional models), organized by asset class group. These statistics are computed over the sub-periods 2013–2016, 2017–2019, and 2020–2022.

5.2.1 First sub-period: 2013–2016

During the first sub-period, encompassing 815 observations, the returns of various asset classes exhibited similar behaviors. The minimum returns ranged from −6.54% to −14.97%, with *Metals* and *Equity* assets displaying greater downside risk. On the other hand, *Agriculture* had the least negative returns. The average returns over this period showed that all asset classes delivered on average negative performance. Maximum returns, ranging from 10.15% to 16.20%, indicate moderate spikes, with *Metals* and *TTFFut* showing higher returns. Standard deviation varies across asset classes, with *TTFSpot* denoting the higher volatility.

Minimum values for the conditional volatility range from 0.35% to 1.27%, with *Equity* assets exhibiting the lowest volatility and *TTFSpot* the highest. The average (annualized) conditional volatility ranges, for all asset classes, between 18.35% and 42.54%. *TTFFut* and *TTFSpot* display the highest volatility. The maximum conditional volatility ranges between 4.13% for *Agriculture* and 7.09% for *Metals*. *TTFFut* and *TTFSpot* show the largest standard deviation of conditional volatilities.

5.2.2 Second sub-period: 2017–2019

In the second sub-period, comprising 754 observations, minimum returns range from -6.49% to -77.34%, with *TTFSpot* exhibiting extreme downside potential. *Equity* assets display the highest average returns, while *TTFFut* and *TTFSpot* show persistent negative returns. Maximum returns range from 6.39% to 52.22%. Interestingly *TTFFut* and *TTFSpot* show the lowest minimum and the highest maximum return. Standard deviations are low across asset classes, except for TTF.

Conditional volatility within this time-frame witnessed the minimum values ranging from 0.31% to 1.31%, significantly lower than the previous sub-period. The average annualized conditional volatility span from 14.79% for *Equity* to 61.05% for *TTFSpot* with *TTFFut* being the second. The maximum conditional volatility shows strong heterogeneity between the commodities and the two TTF proxies stand out with double digits volatility values. Standard deviations of conditional volatilities were comparable to the previous sub-period, except for *TTFSpot* and *TTFFut* where we observe an increase.

5.2.3 Third sub-period: 2020–2022

During the last sub-period, which includes 705 observations, returns exhibit extreme variability and jump-like dynamics. Minimum returns ranged from -10.02% to -56.86%, implying substantial downside risk, particularly for *Energy* assets. Average returns are positive for all commodities and negative for *Equity*; *TTFSpot* and *TTFFut* show extreme positive average returns. Maximum returns are substantially higher than the first and second period, indicating jump-like returns in asset dynamics. Standard deviations of returns are the highest for all asset classes, with *TTFSpot* and *TTFFut* being the most volatile.

Conditional volatility is characterized by minimum values between 0.34% and 2.22%. *Equity* and *TTFSpot* exhibit, respectively, the lowest and the highest average conditional volatility. Maximum conditional volatility, in line with the minimum, persists over time. Standard deviations of conditional volatilities are the highest.

As the statistics denote, this is the sub-period in which extreme events materialized. The Covid-19 in 2020 and the Russia-Ukraine in 2021 set the course of commodity and financial markets, with unprecedented return and volatility impacts. This is the most complex sub-period which also induced the European authorities to introduce price caps mechanisms to tame spikes in gas prices.

5.3 Correlation Analysis

To inspect and uncover relationships among all commodity and financial assets we run a correlation analysis. Major results are synthesized in Figure 6, which depicts different correlation measures across all assets.

Observe, first, how *TTFFut* appear to be, on average, less correlated with other assets. However, we do observe some degree of correlation between *TTFFut* and some commodities within the Energy class.

Equity indices exhibit only modest correlations with commodities, while they are positively correlated among them. This is consistent with recent evidence showing a decrease in the diversification benefit due to increasing correlations among international equity markets (Longin and Solnik (1995); Errunza et al. (1999); Driessen and Laeven (2007)).

Commodities exhibit spikes in (positive) correlations, then indicating a systematic component in their covariance structure. Note that some commodity indices overlap one each others or with single commodities, resulting in strong positive correlations. On this regard, we do not inspect whether such an overlap implies any "causal effect" between assets, since our conditional models are univariate and designed to capture individual asset dynamics without assuming specific directional influences.

Table 2 offers a comprehensive overview of the correlations between *TTFFut* and other assets. The first three columns report Pearson, Kendall, and Spearman correlation coefficients, respectively. Pearson's correlation suggests a modest positive correlation between *TTFFut* and several assets, such as *Energy*, *Gasoil*, *BrentCrudeOil*, and *CrudeOil*, indicating that *TTFFut* tends to move linearly in the same direction with these commodities. On the other hand, there is no linear correlation between *TTFFut* and assets like *Gold*, *Silver*, and several global stock market indices (e.g., *Germany*, *UK*, *India*). Kendall and Spearman correlations, which assess non-linear relationships, generally confirm the findings of the Pearson correlations.

The last three columns display correlation measures coming from the ARMA(1,1)-GARCH(1,1), ARMA(1,1)-EGARCH(1,1), and ARMA(1,1)-GJR(1,1) models. Notably, these models often produce correlation values similar to the traditional correlation measures (Pearson, Kendall, Spearman). This suggests that linear and rank-based correlations may capture core co-movements in asset dynamics. To summarize, Energy-related assets exhibit the strongest positive correlation with *TTFFut*, while precious metals show weak or negative correlation. The correlation between *TTFFut* and global stock market indices varies from positive to close-to-zero correlation.

In Figure 5 we show the 250-day rolling Pearson correlations between the returns of *TTFFut* and other assets. The figure highlights clear correlation regimes between *TTFFut* and the other assets, with periods characterized by relatively low or even negligible correlation followed by positive correlation. This is the case, specifically, for *TTFSpot*. The correlation between *TTFFut* and *TTFSpot* is substantial, although exhibiting high variability over time. Low to positive correlation periods alternate almost every two years, suggesting close-to regular correlation cycles. Post-early 2022, a substantial shift affects all the correlations: *TTFFut* is strongly (and positively) correlated with energy-related commodities, indicating heightened inter-dependence within this sector, while correlations with equity indices took a strong negative turn. Such a change in co-movement dynamics for *TTFFut* can be explained by the inner structure of the correlation itself, being factorizable in two components: (i) a first spurious correlation component which arises when asset correlations tend to become more high during market stress and flight-to-quality phenomena due to increased systematic risk perception; (ii) a second idiosyncratic correlation component, which governs structural shift in asset correlations with *TTFFut*, which seems to play a pivotal role during the Russia-Ukraine conflict.

6 Results

In this section, we present the results of our simulation analysis. We first explore the predicted *TTTFut* dynamics, focusing on the different scenarios generated through simulation. Second, we execute the comparative analysis using ANOVA to test differences across asset class, price-caps and simulation methods. Results are presented by main ownership asset class.

In Table 3 we preliminary report the number of states of the world which obey to the price cap mechanisms. These numbers are interesting as they tell us about the price-cap pervasiveness. Note that when Fixed Price Cap mechanism is at play, only $1,142$ ad 743

(FHS and EVT) out of $15,000$ are retained, namely around 6 per cent: this signifies that the probability to activate the Fixed Price Cap mechanism is about 94 per cent, thereby suggesting tight constraining mechanism imposed on price dynamics. On the other hand, the Institutional mechanism seems to be less pervasive, as the number of states of the world are $13,050$ and $12,842$, corresponding to near 86 per cent of the possible expected prices: the probability to activate the Institutional Price Cap mechanism is therefore about 14 per cent. Our Dynamic Price Cap is in the middle, as the number of states are $10,637$ and $10,991$ corresponding to 72 per cent of possible price paths to be considered as potentially moving under volatility (and price level) control: this signifies that the probability to activate the Dynamic Price Cap mechanism is about 28 per cent.

6.1 *TTFFut* Dynamics

We now explore the dynamics of *TTFFut* price and conditional volatility, both in their unconstrained and constrained forms, providing important insights into how price caps impact the shape of *TTFFut* forecasts.

6.1.1 *TTFFut* Prices

Figure 7, shows the dynamics of *TTFFut* prices under different scenarios and simulation methods.

Plots (1,1) and (1,2) denote minimal differences between FHS and EVT methods. The forecasts under both methods exhibit similar trends, with a right-skewed price distribution. Notably, the forecasted price trajectory rises toward the upper tail, indicating expected price increases. The third quartile at the end of the forecasting window aligns with the first peak price in the time window displayed on the plots recorded on March 2022.

Also plots (2,1) and (2,2) denote subtle differences between FHS and EVT. Under the FS mechanism, the price path is quite stable over time. Comparing this scenario with the BS, we observe lower prices, converging towards the median. Notably, FHS exhibits irregular quartiles, which may be linked to variability in the relatively small number of states of the world retained when the price cap is in force. Conversely, EVT displays more regular quartiles, with a relatively symmetric distribution of price forecasts.

Plots (3,1) and (3,2) show negligible differences between FHS and EVT methods. The

IS scenario seems to mitigate the skewness of predicted price caps compared to the BS, with the third quartile of price estimates lower and closer to the 200 USD/MWh upper limit. As a whole, IS price forecasts appear to exhibit only minimal differences from those of the BS.

Finally, plots (4,1) and (4,2) show price dynamics in the DS case. Here, the Ibbotson's cone shows even less right-skewness in price forecasts compared to the IS and the BS. The third quartile falls short of the 200 USD/MWh upper limit, thus indicating a low volatility market. Remarkably, FHS estimates tend to reach lower price forecasts compared to EVT, with non-linear quartiles. Notably, the FHS plot under the DS reveals a narrowing trend in quartiles towards the end of the forecasting period.

6.1.2 *TTFFut* Conditional Volatility

Plots (1,1) and (1,2) in Figure 8 show the daily conditional volatility under the BS. As for the prices, FHS and EVT methods deliver similar results. Some difference appears only at the outset, where the Ibbotson's cone appears slightly larger for FHS. In both cases, the conditional volatility forecasts imply a market volatility that tends to calm down over time: as for the prices the forecasted daily conditional volatility distribution is right-skewed indicating substantial probability of upper spikes. These spikes are substantial for both FHS and EVT, but the distance between the third quartile and the median seem to be more high in the case of FHS.

Plots (2,1) and (2,2) provide insight into the complex picture of FS scenario. In the case of FHS, quartiles display notable non-linear patterns. This is because of relatively smaller number of surviving states of the world under this price cap compared to other scenarios. On the other hand, EVT displays more regular quartiles. As a whole, we observe a significant constraining effect on *TTFFut* dynamics, resulting in a lower implied probability of the FS scenario discounted by the market.

Plots (3,1) and (3,2) depict the IS scenario, where differences in conditional volatility between FHS and EVT are relatively small. Both methods show similar volatilities relative to BS, suggesting that the institutional price cap have a negligible impact on *TTFFut* volatility.

Finally, plots (4,1) and (4,2) are for expected conditional volatility dynamics under the DS mechanism. In this scenario, the Ibbotson's cone is narrower compared to other scenarios and is similar with the FS, although it exhibits more regular and narrow quartiles. Interestingly, note that the cone's size is relatively larger at the beginning of the forecasting window. As time passes, in particular since January 2023, the cone shrinks, specifically with FHS.

6.2 Comparative Analysis

In Tables 4, 6, and 8 we report results of the ANOVA tests run on cumulative returns, mean and median conditional volatility. As explained in Section 4.3, with these tests we examine group differences and their interactions between scenarios, simulation methods, and conditional models, while aggregating the results at the asset class level. More detailed results are in the Appendix, where we present two-way ANOVA tests and asset-specific results.

As a whole, factors and interaction terms significantly contribute in group differences. For cumulative returns as well as for mean and median conditional volatilities, differences appear statistically significant (all p-values < 0.01), also when considering individual factors and their combination, as reported in Tables 5, 7 and 9 showing Tukey's honestly significant procedure. Hence, all price cap mechanisms implemented on *TTFFut* have a significant impact on price and volatility dynamics of commodities and equity indices. Conditional model comparison for both cumulative returns and mean-median volatility reveals significant differences among GARCH, EGARCH and GJR in volatility, thereby proving the key role played by the conditional models in shaping the predicted conditional volatility. For cumulative returns only EGARCH differs significantly from the others.

An in-depth analysis of differences across price cap-asset class-simulation methods-conditional models reveals more detailed findings for both cumulative returns and mean-median volatility.

Let us start with ANOVA tests on cumulative returns reported in Table 5:

- Scenario differences are all significant, with all p-values close to zero. Each cap mechanism leads to significant price reduction (see all differences $BS - FS$; $BS - IS$; $BS - DS$) with the Fixed Price Cap mechanism exerting the higher impact (see $FS - IS$; $FS - DS$), followed by our Dynamic Price Cap mechanism; the Institutional mechanism has the lower price impact ($IS - DS$).

- The comparison between simulation methods denotes higher negative price impact when using EVT (the difference between FHS and EVT is positive and statistically significant). This is consistent with the inner mechanism of EVT, which gives more weight on extreme (tail) negative returns. From a policy perspective, employing both non-parametric historical block sampling and parametric numerical simulation – where we consider the non-negligible probability of concurrent extreme price scenarios – provides a more comprehensive overview of all potential outcomes. This includes cases where historical co-movements repeat themselves and situations where new extreme scenarios could occur.

- All price caps negatively impact commodity market returns. Notably, the *Energy* asset class is the most price cap sensitive category. Under the Fixed Price Cap, *Energy*, delivers a cumulative return of 19.52% less than the Baseline Scenario. Similar patterns are for *Metals* and *Agriculture*, albeit to a lesser extent, with differences from the Baseline Scenario of 2.98% and 5.30%, respectively. The Institutional Price Cap has low impact for both *Metals* and *Agriculture*. The Dynamic Price Cap, while reducing expected returns more than the Institutional price cap, has approximately half of the Fixed Price cap impact.

- The expected impact on *Equity* markets is negative for all price cap mechanisms relative to the Baseline (see all differences $BS - FS$; $BS - IS$; $BS - DS$ in Table 5, panel "Scenario & Asset Class"). In other words, an analysis of expected impacts on equity markets connected with the introduction of a gas price cap mechanism, by taking into account the entire dependence structures between commodity and equity indices, leads to an overall negative expected impact relative to the Baseline Scenario, namely relative to a world without a price cap mechanism. The major negative expected impact is with the Fixed Price mechanism, whose difference with the Baseline Scenario[13] is 1.90%. The Institutional Scenario denotes the less negative expected impact with a difference relative to the Baseline of 0.30%. Similarly, the impact for Dynamic Price cap is 0.65%. The less negative expected impact with the Institutional mechanism is because such a price cap is not so different relative to the Baseline. Indeed, as we commented in Section 6, the Institutional mechanism

[13]The difference is computed using the means of FHS and EVT from both scenarios.The Tables are available in the Appendix.

seems to be the less pervasive, as the number of states of the world are near 86 per cent of the baseline expected prices.

Consider now ANOVA tests on mean and median conditional volatility reported in Tables 7 and 9:

- Only our Dynamic Price Cap exerts significant impact on volatility, as the values for mean and median volatility are lower than the Baseline Scenario, Fixed Price Cap, and Institutional Scenarios. For other cap mechanisms we have mixed results: Fixed Price Cap and Institutional Price Cap Scenarios denote significant mean volatility impacts, but not for median. As a whole, we then conclude that only the Dynamic Price Cap has a clear and significant volatility impact on all other commodity and equity assets.

- When exploring interactions with asset class, the Dynamic Price Cap confirms to be the only one to exert an impact on volatility, which is significantly lesser than that shown by other cap methods, except for *Metals* and *Agriculture*, when comparing the mechanism with the Fixed Price Cap: in this case the difference in volatility is close to zero. Nevertheless, for both asset classes the Dynamic Price Cap results are different and statistically significant from the Baseline. This does not hold when comparing the Fixed Price Cap with Baseline Scenarios for *Agriculture*.

- As it is the case for cumulative returns, also here we have different impact estimation when using FHS or EVT. The difference $FHS - EVT$ is negative, denoting higher conditional volatility for EVT. This is due to the parametric approach used by the EVT, which gives more weights on extreme returns.

- The impact of the Dynamic Price Cap on equity index volatility is significant, as our estimation regarding the expected volatility lowering on international equity indices is 0.28% (mean) and 0.20% (median) less than the baseline volatility. In all other scenarios, the difference in volatility is either not significant or leads to an increase compared to the Baseline (see the Appendix for more detailed results).

6.3 Discussion

Our findings document substantial expected price and volatility impacts on commodities and equity indices connected with the introduction of a gas price cap mechanism. Taking into account the entire dependence structures between commodity and equity indices, we prove that gas price significantly affects the dynamics not only of other energy commodities, as documented in many studies (Chuliá et al. (2019), Hirth (2018)), but also of equity indices, although with different magnitudes. The fact that between gas price and equity markets there is a, possibly time-varying, relationship is not new. For e.g., Acaravci et al. (2012) document a long-term equilibrium relationship between natural gas prices, industrial production and stock prices in Austria, Denmark, Finland, Germany and Luxembourg; Rizvi et al. (2022) find that gas price negatively affect equity market returns in the short run, while the relationship changes in the long run, as gas seems to subside it substantially. The novelty of our results is about the quantification of the expected price cap impact on commodity and equity markets:

- Energy-related commodities are the most sensitive to regulatory price intervention, both for price and conditional volatility impacts. A fixed price cap has a strong significant price impact, but the volatility remains largely unaffected (FHS), or, in few cases documented by EVT, shows an increase in volatility.

- A dynamic price cap directly linked to TTF volatility reduces energy commodity prices together with their volatility (for both FHS and EVT cases). The same results hold for metals and agricultural commodities. The current mechanism implemented by the European Commission seems less pervasive than pure fixed and dynamic price caps, however exerting a significant price reduction in all asset classes, but it is ineffective as volatility lowering tool.

- All price caps on the *TTFFut* are expected to impact negatively on equity returns in different ways: 1-year return of the European equity index is expected to move from moderately positive – the value is 0.32%[14] with no cap rule (Baseline) – to strongly negative with a fixed price cap – the value is -3.53% (here the difference between FS and BS expected returns is statistically significant). The expected return is negative

[14] All the individual asset values for expected cumulative returns and mean/median conditional volatility at the individual asset level are in the Appendix.

also for the current mechanism adopted by the European Commission with -0.11%, and for our dynamic cap alternative with -1.14%, but in both cases the difference is not statistically significant from the BS results. For all other equity indices the sign of expected return are the same, by comparing capping with no capping mechanisms, but all price caps reduce/worsen the expected positive/negative returns.

- We document a significant negative impact of fixed and dynamic caps on the returns of the following country indices: *UK*, *France*, *Italy*, *Canada* and *Spain*. On the other side *China* shows a significant returns increase only in the Dynamic Price Cap Scenario (see Appendix). The median conditional volatility is expected to significantly increase for *Italy*, *Russia*, *Canada* and *Spain* when comparing the Fixed Price Cap with the Baseline Scenario. When comparing Dynamic Price Cap with the Baseline, mean and median conditional volatility of *Global*, *Europe*, *USA*, *China*, *Germany*, *UK*, *France*, *Russia* and *Canada* are expected to decrease, while returns of *France*, *UK* and *Canada* worsen significantly. As our analysis processed all commodity and equity data together, expected positive and negative equity returns combine different transmission channels:

    1. **Expected cash flows.** Commodity prices are a major cost/revenue factor in various economic activities and used as risk factors in many asset pricing models (Ando and Bai (2015)). The theoretical linkage between stock prices and key commodity price can be expressed as in Huang et al. (1996), who inspect how oil price is linked with the stock price. Since stock prices are discounted values of expected future cash flows, returns are affected by systematic movements in expected cash flows and discount rates. Following this reasoning, gas price changes, and connected commodities, could alter firms' future cash flows either positively or negatively, depending on whether the gas is a cost or revenue factor. For firms using gas as no perfect substitute cost factor, an increase in gas prices will result in an increase of production costs, which, in turn, will reduce future cash flows. When gas is a revenue factor, the firm increase profits when gas price rises then resulting in increased expected cash flows. Based on this argument, *China*, *USA*, *Japan*, *India*, *Germany* may not be affected or even benefit from the rise in gas prices being a country in which gas plays a role of net-revenue factor. On the other hand, gas might play a

net-cost factor for *UK*, *France*, *Italy*, *Canada* and *Spain*. Instead, the very negative expected returns in the Baseline Scenario for *Russia* reflect major macroeconomic negative impacts, due to international sanctions and economic consequences of war, albeit the effects of caps on its returns are not statistically significant.

2. **Discount rates**. As pointed out in Huang et al. (1996), the expected discount rate used in discounting future cash flows is composed of the expected inflation rate and the expected real interest rate. Both components may depend on expected gas prices. As a result, gas price rises could impact discount rates through expected inflation and expected real interest rates: higher expected inflation rate is positively related to the discount rate and, in turn, reflect on negative stock returns. Moreover, under high inflation regimes, short-term interest rates are expected to rise in all countries where policy target of central banks is to stabilize the economy and price levels. As discussed in Degiannakis et al. (2018) there are two main effects of the increased short-term interest rates on stock markets: (i) commercial borrowing rates rise, then reflecting on higher discount rates; (ii) increased borrowing rates reflect on lower cash flows. In both cases, stock prices decrease in value.

These findings rather than opening the question whether the European gas price cap currently in force is with a too high or low price cap, suggest that a better way to prevent gas market turmoils with connected spillover effects on other commodity and stock market assets, is through a mechanism based on volatility dynamics instead of the price itself, as the one proposed in this paper. Moreover, the methodological approach we propose to assess the expected impact of price cap mechanism, which is based on Filtered Historical- and Extreme Value Theory-based simulations, permits to quantify within a cost-benefit analysis all impacts in commodity and equity markets related to policy intervention options. As is obvious, this is particularly useful for regulators, as they can assess positive and negative impacts from specific policy interventions. It is useful for investors alike, as the ex-ante estimation of means, volatilities and all dependencies (co-movements and copulae) among commodities and equity indices can help realize very diversified, and possibly hedge, portfolios. This is what we will inspect in our future research agenda.

7 Conclusions

This study quantifies the expected impacts of alternative gas price caps on the European natural gas spot price using a simulation-based approach over the period from 2013 to 2023.

Without any price cap mechanism, the European TTF Gas price was expected to rise, while the majority of energy-related commodity prices decline and agricultural commodities increase; mixed expected results are for metals and equity markets. A price cap mechanism is expected to impact negatively on all commodities and equity market returns.

When exploring alternative price cap mechanisms, we find that a fixed price cap has the higher price impact, however with poor power in lowering the price volatility. Interestingly, the European gas price cap currently in force seems to be less pervasive and ineffective as volatility lowering tool, however exerting a significant price reduction in all asset classes.

Instead, a price cap mechanism which imposes a limit on the conditional expected volatility of the TTF month-ahead gas price through quantile-based stability criteria proves to be more effective in preventing gas market turmoils and connected volatility spillover effects on other commodity and stock market assets.

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A Tables

Table 1: Descriptive statistics of returns and conditional volatilities

Class	**Agricolture**	**Energy**	**Equity**	**Metals**	**TTFFut**	**TTFSpot**
Num	17	9	13	15	1	1
			Returns			
2013 - 2016: 815 Obs						
Min	-0.0654	-0.1080	-0.1497	-0.1604	-0.1248	-0.1050
*Avg**	-0.2470	-0.5282	-0.0241	-0.1806	-0.3325	-0.2825
Max	0.1085	0.1015	0.1193	0.1620	0.1474	0.1055
*Std**	0.2094	0.3548	0.1969	0.2231	0.3218	0.3928
2017 - 2019: 754 Obs						
Min	-0.0649	-0.1918	-0.1304	-0.1359	-0.1318	-0.7734
*Avg**	0.0782	0.0533	0.2302	0.1631	-0.4834	-0.4626
Max	0.0639	0.1664	0.0592	0.0851	0.3170	0.5222
*Std**	0.2051	0.2919	0.1412	0.2022	0.4760	0.8889
2020 - 2022: 705 Obs						
Min	-0.1002	-0.5686	-0.4669	-0.2382	-0.3524	-0.4321
*Avg**	0.3533	0.4585	-0.1793	0.1325	2.2402	1.6140
Max	0.0956	0.3201	0.2291	0.4960	0.4128	0.3502
*Std**	0.2636	0.5638	0.2900	0.3138	1.0264	1.1803
			Conditional Volatility			
2013 - 2016: 815 Obs						
Min	0.0053	0.0075	0.0035	0.0059	0.0088	0.0127
*Avg**	0.2060	0.3453	0.1835	0.2181	0.3285	0.4254
Max	0.0413	0.0534	0.0615	0.0709	0.0610	0.0612
Std	0.0041	0.0083	0.0050	0.0053	0.0087	0.0096
2017 - 2019: 754 Obs						
Min	0.0054	0.0098	0.0031	0.0049	0.0116	0.0131
*Avg**	0.2022	0.2944	0.1479	0.2044	0.4328	0.6105
Max	0.0289	0.0753	0.0434	0.0525	0.1265	0.4079
Std	0.0038	0.0062	0.0032	0.0046	0.0147	0.0391
2020 - 2022: 705 Obs						
Min	0.0058	0.0114	0.0034	0.0045	0.0201	0.0222
*Avg**	0.2369	0.4677	0.2277	0.2715	0.8902	1.0008
Max	0.0518	0.2168	0.1743	0.1214	0.2134	0.2335
Std	0.0057	0.0184	0.0099	0.0080	0.0311	0.0366

The table reports summary statistics for the assets over the sub-periods 2013–2016, 2017–2019, 2020–2022: *Avg* is the average. *Min* and *Max* are the minimum and the maximum, respectively. *Std* is the standard deviation. * denotes annualized values. The conditional volatility has been averaged over the three conditional models.

Table 2: Correlation measures between *TTFFut* and other assets

Asset	**Pearson**	**Kendall**	**Spearman**	**GARCH**	**EGARCH**	**GJR**
AllCrude	0.1298	0.0961	0.1406	0.1639	0.1667	0.1643
BrentCrudeOil	0.1430	0.1005	0.1475	0.1714	0.1734	0.1719
CrudeOil	0.1147	0.0912	0.1337	0.1542	0.1574	0.1539
Energy	0.1555	0.1119	0.1642	0.1798	0.1827	0.1804
Gasoil	0.2045	0.1388	0.2015	0.2163	0.2160	0.2173
HeatingOil	0.1997	0.1190	0.1743	0.1859	0.1869	0.1861
NaturalGas	0.1009	0.0703	0.1027	0.0707	0.0771	0.0713
Petroleum	0.1475	0.1053	0.1543	0.1740	0.1767	0.1744
UnleadedGasoline	0.1239	0.0940	0.1378	0.1339	0.1369	0.1354
AllMetals	0.0645	0.0285	0.0413	0.0478	0.0479	0.0471
Aluminum	0.0726	0.0322	0.0469	0.0454	0.0470	0.0459
Copper	0.0269	0.0331	0.0481	0.0571	0.0555	0.0547
Gold	-0.0004	-0.0305	-0.0453	-0.0296	-0.0320	-0.0305
IndustrialMetals	0.0776	0.0430	0.0622	0.0663	0.0663	0.0655
IronOre	0.0655	0.0183	0.0276	0.0303	0.0348	0.0306
Lead	0.0547	0.0223	0.0330	0.0523	0.0520	0.0519
Nickel	0.0852	0.0334	0.0496	0.0532	0.0528	0.0532
NorthAmericanCopper	0.0222	0.0271	0.0396	0.0467	0.0461	0.0449
Palladium	0.0556	0.0179	0.0268	0.0304	0.0318	0.0310
Platinum	-0.0253	-0.0026	-0.0039	-0.0057	-0.0081	-0.0056
PreciousMetals	-0.0042	-0.0331	-0.0490	-0.0317	-0.0334	-0.0315
Silver	-0.0211	-0.0309	-0.0453	-0.0298	-0.0293	-0.0297
Tin	0.0423	0.0202	0.0300	0.0307	0.0332	0.0297
Zinc	0.0857	0.0229	0.0342	0.0506	0.0498	0.0509
Agriculture	0.0864	0.0201	0.0300	0.0392	0.0402	0.0404
AgricultureLivestock	0.0711	0.0141	0.0207	0.0301	0.0320	0.0311
AllCattle	-0.0305	-0.0114	-0.0172	-0.0232	-0.0233	-0.0259
AllWheat	0.1098	0.0159	0.0237	0.0323	0.0316	0.0329
Cocoa	-0.0052	0.0078	0.0109	0.0137	0.0152	0.0145
Coffee	0.0317	0.0269	0.0399	0.0416	0.0448	0.0450
Corn	0.0450	0.0044	0.0064	0.0110	0.0089	0.0097
Cotton	0.0236	0.0314	0.0456	0.0506	0.0506	0.0521
FeederCattle	-0.0252	-0.0038	-0.0056	-0.0083	-0.0052	-0.0079
Grains	0.0819	0.0151	0.0222	0.0284	0.0287	0.0291
KansasWheat	0.1041	0.0182	0.0270	0.0350	0.0338	0.0355
LiveCattle	-0.0307	-0.0131	-0.0195	-0.0260	-0.0275	-0.0288
Livestock	-0.0310	-0.0099	-0.0154	-0.0183	-0.0161	-0.0206
Softs	0.0376	0.0294	0.0437	0.0523	0.0548	0.0549
SoybeanOil	0.0358	0.0383	0.0559	0.0541	0.0609	0.0564
Soybeans	0.0319	0.0155	0.0225	0.0264	0.0301	0.0290
Wheat	0.1110	0.0157	0.0233	0.0307	0.0313	0.0314
Canada	0.0125	0.0290	0.0424	0.0680	0.0697	0.0697
China	0.0124	0.0279	0.0416	0.0477	0.0489	0.0479
Europe	-0.0649	0.0154	0.0222	0.0376	0.0360	0.0359
France	-0.0680	0.0146	0.0210	0.0318	0.0299	0.0308
Germany	-0.0822	0.0103	0.0144	0.0279	0.0274	0.0277
Global	-0.0129	0.0238	0.0340	0.0481	0.0506	0.0475
India	-0.0393	0.0046	0.0062	0.0140	0.0196	0.0133
Italy	-0.0559	0.0172	0.0251	0.0440	0.0429	0.0431
Japan	-0.0355	-0.0122	-0.0175	-0.0175	-0.0178	-0.0169
Russia	-0.1500	0.0324	0.0474	0.0694	0.0725	0.0708
Spain	-0.0576	0.16.9	0.0245	0.0405	0.0414	0.0418
UK	-0.0329	0.0282	0.0409	0.0603	0.0610	0.0599
USA	0.0086	0.0280	0.0404	0.0406	0.0447	0.0436

The table shows historical correlation between *TTFFut* and other assets using different approaches. The first column shows the Pearson correlation coefficient. The second column shows the Kendall correlation coefficient. The third column shows the Spearman correlation coefficient. The last three columns show the dependence structure from t-copula based standardized residuals of ARMA(1,1)-GARCH(1,1), ARMA(1,1)-EGARCH(1,1) and ARMA(1,1)-GJR(1,1).

Table 3: States of the world and price cap scenarios

Scenario	**Method**	**GARCH**	**EGARCH**	**GJR**	**Total**
BS	*FHS*	5000	5000	5000	15000
BS	*EVT*	5000	5000	5000	15000
FS	*FHS*	365	416	361	1142
FS	*EVT*	242	244	257	743
IS	*FHS*	4344	4417	4289	13050
IS	*EVT*	4233	4295	4314	12842
DS	*FHS*	3501	3632	3504	10637
DS	*EVT*	3602	3734	3655	10991

The table reports the number of states of the world for each cap mechanism, and for each conditional model also splitting by simulation method, for which the predicted TTF front-month price (or volatility, when focusing on the Dynamic Proce Cap scenario) in any of those states of the world comply with the cap mechanism under scrutiny.

Table 4: N-way ANOVA tests on cumulative returns

Source	**Sum Sq.**	**d.f.**	**Mean sq.**	**F**	**Prob > F**
Scenario	1160.9794	3	386.9931	3605.9814	0.0000
AssetClass	3720.6216	3	1240.2072	11556.1850	0.0000
Method	7.2489	1	7.2489	67.5449	0.0000
Model	2.3273	2	1.1637	10.8430	0.0000
Scenario:AssetClass	719.8746	9	79.9861	745.3059	0.0000
Scenario:Method	624.2357	3	208.0786	1938.8651	0.0000
Scenario:Model	14.9592	6	2.4932	23.2315	0.0000
AssetClass:Method	814.6422	3	271.5474	2530.2643	0.0000
AssetClass:Model	27.5043	6	4.5841	42.7140	0.0000
Method:Model	40.4969	2	20.2485	188.6741	0.0000
Error	460169.0686	4287831	0.1073		
Total	471061.3052	4287869			

The table shows n-way ANOVA results performed on forecasted cumulative returns. *Scenario* refers to the price cap mechanism under scrutiny applied on *TTFFut*: BS, is the Baseline Scenario (no price cap). FS denotes the Fixed Price Cap Scenario,IS is the the Institutional Price Cap Scenario, and DS refers to the the Dynamic Price Cap Scenario. *AssetClass* are: Energy, Metals, Agriculture and Equity. *Method* refers to the simulation method: FHS are the Filtered Historical Simulations, and EVT are the Extreme Value Theory-based simulations. *Model* denotes the conditional model (ARMA(1,1)-GARCH(1,1), ARMA(1,1)-EGARCH(1,1) and ARMA(1,1)-GJR(1,1)).

Table 5: Tukey's honestly significant difference procedure: cumulative returns

Group A	Group B	Lower Limit	A-B	Upper Limit	P-value
		Scenario			
BS	*FS*	0.0714	0.0742	0.0771	0.0000
BS	*IS*	0.0079	0.0089	0.0099	0.0000
BS	*DS*	0.0341	0.0351	0.0362	0.0000
FS	*IS*	-0.0682	-0.0653	-0.0624	0.0000
FS	*DS*	-0.0420	-0.0391	-0.0362	0.0000
IS	*DS*	0.0251	0.0262	0.0273	0.0000
		Asset Class			
Energy	*Metals*	-0.1484	-0.1461	-0.1439	0.0000
Energy	*Agriculture*	-0.1492	-0.1470	-0.1448	0.0000
Energy	*Equity*	-0.1187	-0.1164	-0.1140	0.0000
Metals	*Agriculture*	-0.0027	-0.0008	0.0011	0.6758
Metals	*Equity*	0.0278	0.0298	0.0318	0.0000
Agriculture	*Equity*	0.0286	0.0306	0.0326	0.0000
		Method			
FHS	*EVT*	0.0037	0.0048	0.0059	0.0000
		Model			
GARCH	*EGARCH*	-0.0048	-0.0032	-0.0015	0.0000
GARCH	*GJR*	-0.0027	-0.0011	0.0006	0.2914
EGARCH	*GJR*	0.0005	0.0021	0.0038	0.0065
		Scenario & Asset Class			
BS, Energy	*FS, Energy*	0.1863	0.1952	0.2042	0.0000
BS, Energy	*IS, Energy*	0.0203	0.0234	0.0266	0.0000
BS, Energy	*DS, Energy*	0.0798	0.0832	0.0865	0.0000
FS, Energy	*IS, Energy*	-0.1808	-0.1718	-0.1628	0.0000
FS, Energy	*DS, Energy*	-0.1211	-0.1121	-0.1030	0.0000
IS, Energy	*DS, Energy*	0.0563	0.0597	0.0632	0.0000
BS, Metals	*FS, Metals*	0.0229	0.0298	0.0367	0.0000
BS, Metals	*IS, Metals*	0.0011	0.0036	0.0061	0.0001
BS, Metals	*DS, Metals*	0.0151	0.0177	0.0203	0.0000
FS, Metals	*IS, Metals*	-0.0331	-0.0262	-0.0192	0.0000
FS, Metals	*DS, Metals*	-0.0191	-0.0121	-0.0051	0.0000
IS, Metals	*DS, Metals*	0.0115	0.0141	0.0168	0.0000
BS, Agriculture	*FS, Agriculture*	0.0465	0.0530	0.0595	0.0000
BS, Agriculture	*IS, Agriculture*	0.0034	0.0057	0.0080	0.0000
BS, Agriculture	*DS, Agriculture*	0.0307	0.0331	0.0356	0.0000
FS, Agriculture	*IS, Agriculture*	-0.0538	-0.0473	-0.0407	0.0000
FS, Agriculture	*DS, Agriculture*	-0.0264	-0.0199	-0.0133	0.0000
IS, Agriculture	*DS, Agriculture*	0.0249	0.0274	0.0299	0.0000
BS, Equity	*FS, Equity*	0.0116	0.0190	0.0264	0.0000
BS, Equity	*IS, Equity*	0.0004	0.0030	0.0057	0.0086
BS, Equity	*DS, Equity*	0.0038	0.0065	0.0093	0.0000
FS, Equity	*IS, Equity*	-0.0234	-0.0160	-0.0085	0.0000
FS, Equity	*DS, Equity*	-0.0200	-0.0124	-0.0049	0.0000
IS, Equity	*DS, Equity*	0.0007	0.0035	0.0064	0.0027

The table shows Tukey's honestly significant difference procedure performed on factors of Table 4.

Table 6: N-way ANOVA tests on mean conditional volatility

Source	**Sum Sq.**	**d.f.**	**Mean sq.**	**F**	**Prob > F**
Scenario	0.0445	3	0.0148	297.4349	0.0000
AssetClass	30.1989	3	10.0663	202060.0857	0.0000
Method	0.1731	1	0.1731	3473.9065	0.0000
Model	0.0368	2	0.0184	368.9298	0.0000
Scenario:AssetClass	0.0076	9	0.0008	17.0469	0.0000
Scenario:Method	0.0336	3	0.0112	224.5440	0.0000
Scenario:Model	0.0032	6	0.0005	10.5768	0.0000
AssetClass:Method	0.1828	3	0.0609	1222.9764	0.0000
AssetClass:Model	0.4203	6	0.0700	1406.0846	0.0000
Method:Model	0.1269	2	0.0635	1274.0559	0.0000
Error	213.6123	4287831	0.0000		
Total	311.9878	4287869			

The table shows n-way ANOVA results performed on forecasted mean daily conditional volatilities.

Table 7: Tukey's honestly significant difference procedure: mean volatilities

Group A	Group B	Lower Limit	A-B	Upper Limit	P-value
		Scenario			
BS	*FS*	0.0000	0.0001	0.0001	0.0599
BS	*IS*	0.0000	0.0000	0.0000	0.0665
BS	*DS*	0.0002	0.0002	0.0002	0.0000
FS	*IS*	-0.0001	-0.0001	0.0000	0.0046
FS	*DS*	0.0001	0.0002	0.0002	0.0000
IS	*DS*	0.0002	0.0002	0.0003	0.0000
		Asset Class			
Energy	*Metals*	0.0108	0.0108	0.0109	0.0000
Energy	*Agriculture*	0.0126	0.0126	0.0127	0.0000
Energy	*Equity*	0.0139	0.0140	0.0140	0.0000
Metals	*Agriculture*	0.0018	0.0018	0.0018	0.0000
Metals	*Equity*	0.0031	0.0032	0.0032	0.0000
Agriculture	*Equity*	0.0013	0.0014	0.0014	0.0000
		Method			
FHS	*EVT*	-0.0008	-0.0007	-0.0007	0.0000
		Model			
GARCH	*EGARCH*	0.0001	0.0002	0.0002	0.0000
GARCH	*GJR*	-0.0003	-0.0002	-0.0002	0.0000
EGARCH	*GJR*	-0.0004	-0.0004	-0.0004	0.0000
		Scenario & Asset Class			
BS, Energy	*FS, Energy*	-0.0002	0.0000	0.0002	1.0000
BS, Energy	*IS, Energy*	-0.0002	-0.0001	0.0000	0.0000
BS, Energy	*DS, Energy*	0.0002	0.0003	0.0004	0.0000
FS, Energy	*IS, Energy*	-0.0003	-0.0001	0.0001	0.9855
FS, Energy	*DS, Energy*	0.0001	0.0003	0.0005	0.0000
IS, Energy	*DS, Energy*	0.0004	0.0004	0.0005	0.0000
BS, Metals	*FS, Metals*	0.0001	0.0003	0.0004	0.0000
BS, Metals	*IS, Metals*	0.0000	0.0000	0.0001	0.9905
BS, Metals	*DS, Metals*	0.0002	0.0002	0.0003	0.0000
FS, Metals	*IS, Metals*	-0.0004	-0.0002	-0.0001	0.0000
FS, Metals	*DS, Metals*	-0.0002	0.0000	0.0001	1.0000
IS, Metals	*DS, Metals*	0.0002	0.0002	0.0003	0.0000
BS, Agriculture	*FS, Agriculture*	0.0000	0.0001	0.0003	0.2076
BS, Agriculture	*IS, Agriculture*	0.0000	0.0000	0.0001	0.9926
BS, Agriculture	*DS, Agriculture*	0.0001	0.0002	0.0002	0.0000
FS, Agriculture	*IS, Agriculture*	-0.0002	-0.0001	0.0000	0.5359
FS, Agriculture	*DS, Agriculture*	-0.0001	0.0000	0.0002	0.9989
IS, Agriculture	*DS, Agriculture*	0.0001	0.0001	0.0002	0.0000
BS, Equity	*FS, Equity*	-0.0003	-0.0001	0.0001	0.6376
BS, Equity	*IS, Equity*	-0.0001	0.0000	0.0000	0.9999
BS, Equity	*DS, Equity*	0.0001	0.0002	0.0002	0.0000
FS, Equity	*IS, Equity*	-0.0001	0.0001	0.0003	0.8646
FS, Equity	*DS, Equity*	0.0001	0.0003	0.0004	0.0000
IS, Equity	*DS, Equity*	0.0001	0.0002	0.0003	0.0000

The table shows Tukey's honestly significant difference procedure performed on factors of Table 6.

Table 8: N-way ANOVA tests on median conditional volatility

Source	**Sum Sq.**	**d.f.**	**Mean sq.**	**F**	**Prob > F**
Scenario	0.0285	3	0.0095	252.2213	0.0000
AssetClass	24.5264	3	8.1755	216933.3875	0.0000
Method	0.1898	1	0.1898	5036.9440	0.0000
Model	0.0104	2	0.0052	138.3228	0.0000
Scenario:AssetClass	0.0070	9	0.0008	20.5033	0.0000
Scenario:Method	0.0206	3	0.0069	181.9776	0.0000
Scenario:Model	0.0010	6	0.0002	4.2585	0.0003
AssetClass:Method	0.3070	3	0.1023	2715.2364	0.0000
AssetClass:Model	0.1887	6	0.0315	834.6756	0.0000
Method:Model	0.0518	2	0.0259	687.5207	0.0000
Error	161.5938	4287831	0.0000		
Total	240.9036	4287869			

The table shows n-way ANOVA results performed on median forecasted daily conditional volatilities.

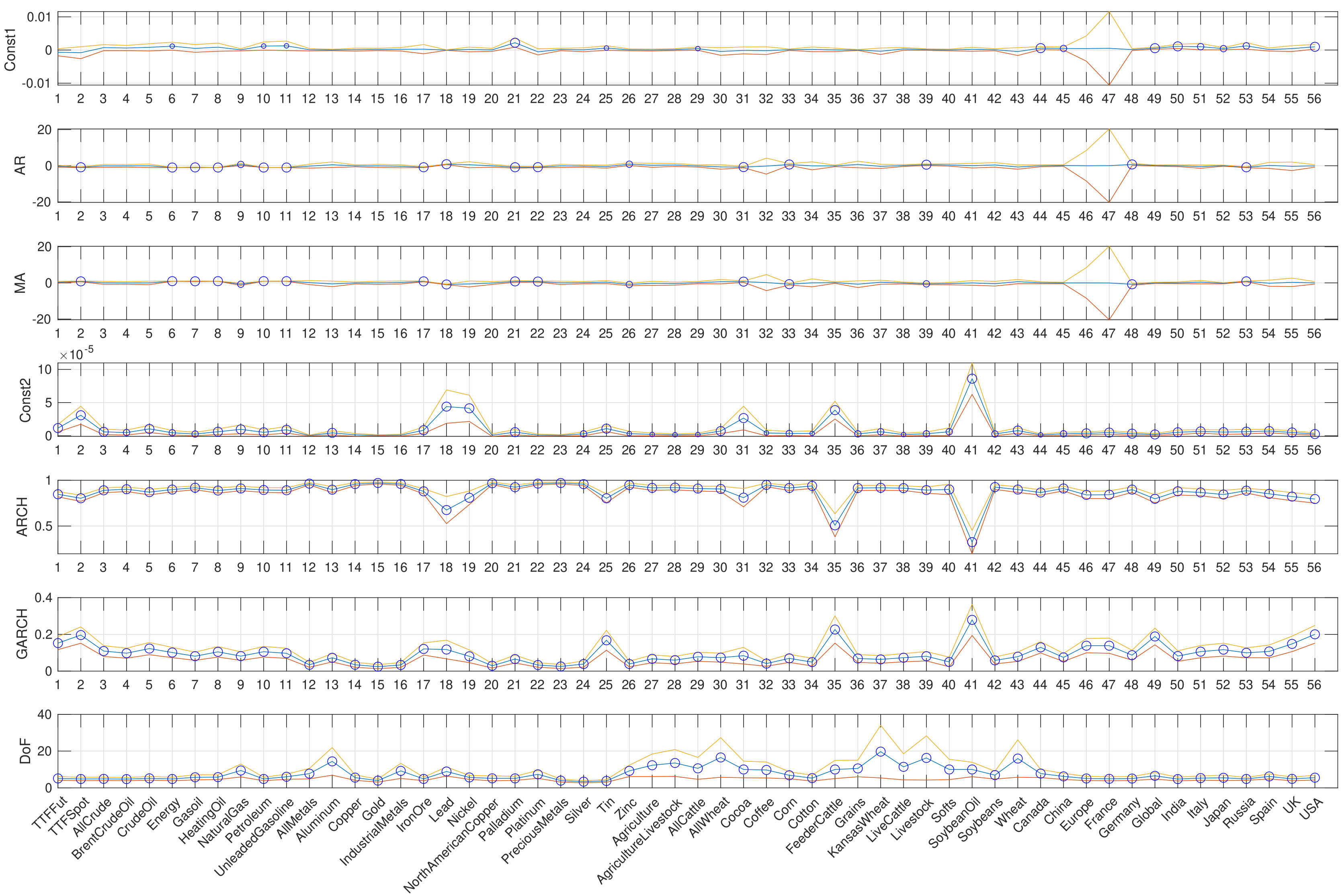
Table 9: Tukey's honestly significant difference procedure: median volatilities

Group A	**Group B**	**Lower Limit**	**A-B**	**Upper Limit**	**P-value**
			Scenario		
BS	*FS*	-0.0001	0.0000	0.0000	0.1303
BS	*IS*	0.0000	0.0000	0.0000	0.2373
BS	*DS*	0.0002	0.0002	0.0002	0.0000
FS	*IS*	0.0000	0.0000	0.0001	0.4311
FS	*DS*	0.0002	0.0002	0.0003	0.0000
IS	*DS*	0.0002	0.0002	0.0002	0.0000
			Asset Class		
Energy	*Metals*	0.0091	0.0091	0.0091	0.0000
Energy	*Agriculture*	0.0108	0.0108	0.0109	0.0000
Energy	*Equity*	0.0130	0.0130	0.0130	0.0000
Metals	*Agriculture*	0.0017	0.0017	0.0018	0.0000
Metals	*Equity*	0.0039	0.0039	0.0039	0.0000
Agriculture	*Equity*	0.0021	0.0022	0.0022	0.0000
			Method		
FHS	*EVT*	-0.0008	-0.0008	-0.0008	0.0000
			Model		
GARCH	*EGARCH*	-0.0002	-0.0002	-0.0002	0.0000
GARCH	*GJR*	-0.0001	-0.0001	-0.0001	0.0000
EGARCH	*GJR*	0.0001	0.0001	0.0001	0.0000
			Scenario & Asset Class		
BS, Energy	*FS, Energy*	-0.0005	-0.0003	-0.0002	0.0000
BS, Energy	*IS, Energy*	-0.0001	-0.0001	0.0000	0.0002
BS, Energy	*DS, Energy*	0.0002	0.0002	0.0003	0.0000
FS, Energy	*IS, Energy*	0.0001	0.0002	0.0004	0.0001
FS, Energy	*DS, Energy*	0.0004	0.0005	0.0007	0.0000
IS, Energy	*DS, Energy*	0.0002	0.0003	0.0004	0.0000
BS, Metals	*FS, Metals*	0.0001	0.0002	0.0003	0.0000
BS, Metals	*IS, Metals*	0.0000	0.0000	0.0001	0.9769
BS, Metals	*DS, Metals*	0.0002	0.0002	0.0003	0.0000
FS, Metals	*IS, Metals*	-0.0003	-0.0002	-0.0001	0.0002
FS, Metals	*DS, Metals*	-0.0001	0.0000	0.0002	1.0000
IS, Metals	*DS, Metals*	0.0002	0.0002	0.0003	0.0000
BS, Agriculture	*FS, Agriculture*	0.0000	0.0001	0.0002	0.0443
BS, Agriculture	*IS, Agriculture*	0.0000	0.0000	0.0001	0.9753
BS, Agriculture	*DS, Agriculture*	0.0001	0.0001	0.0002	0.0000
FS, Agriculture	*IS, Agriculture*	-0.0002	-0.0001	0.0000	0.2160
FS, Agriculture	*DS, Agriculture*	-0.0001	0.0000	0.0001	1.0000
IS, Agriculture	*DS, Agriculture*	0.0001	0.0001	0.0002	0.0000
BS, Equity	*FS, Equity*	-0.0003	-0.0002	0.0000	0.0009
BS, Equity	*IS, Equity*	-0.0001	0.0000	0.0000	1.0000
BS, Equity	*DS, Equity*	0.0001	0.0001	0.0002	0.0000
FS, Equity	*IS, Equity*	0.0000	0.0002	0.0003	0.0037
FS, Equity	*DS, Equity*	0.0002	0.0003	0.0004	0.0000
IS, Equity	*DS, Equity*	0.0001	0.0001	0.0002	0.0000

The table shows Tukey's honestly significant difference procedure performed on factors of Table 8.

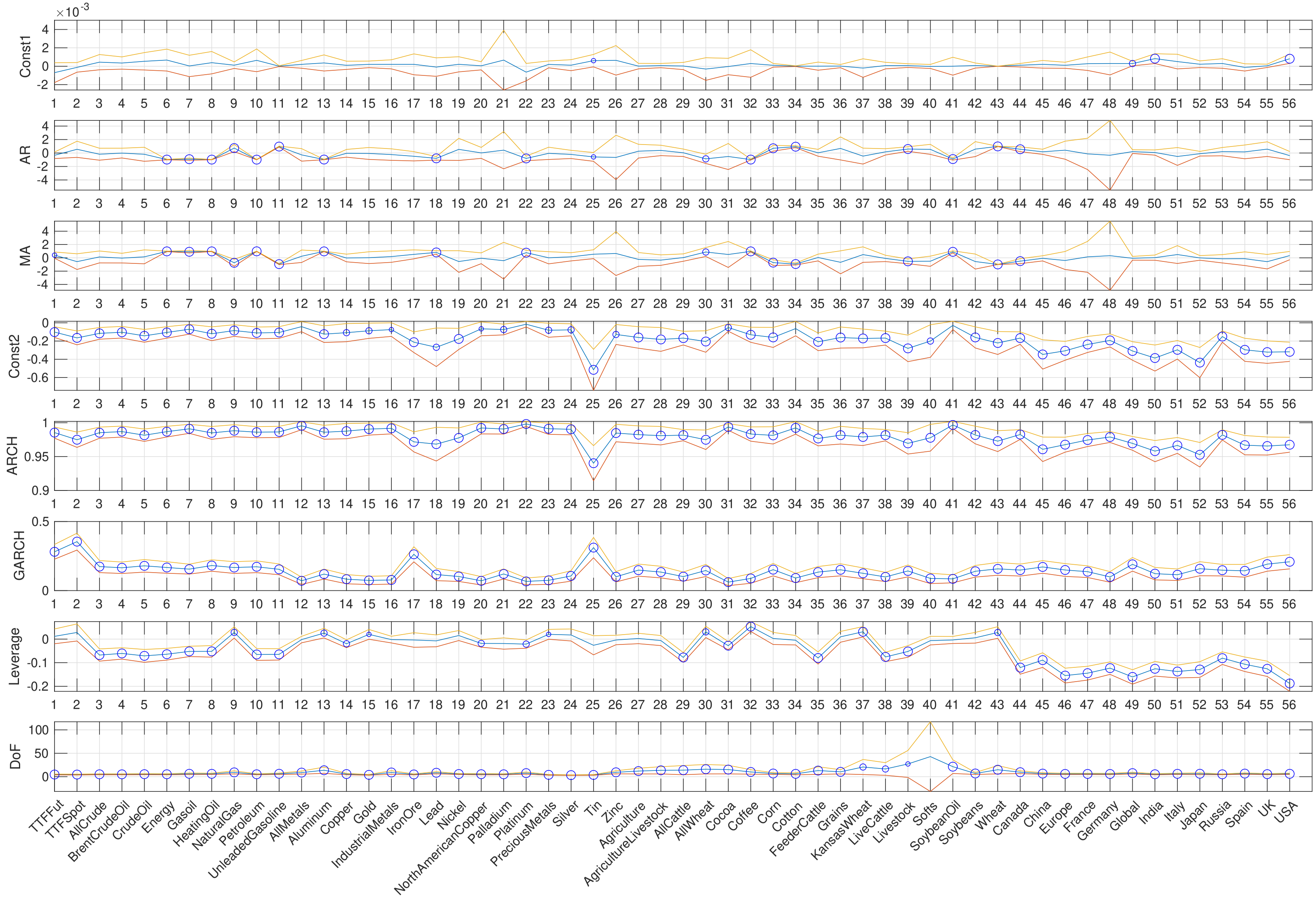
B Figures

Figure 1: ARMA(1,1)-GARCH(1,1) parameter estimates



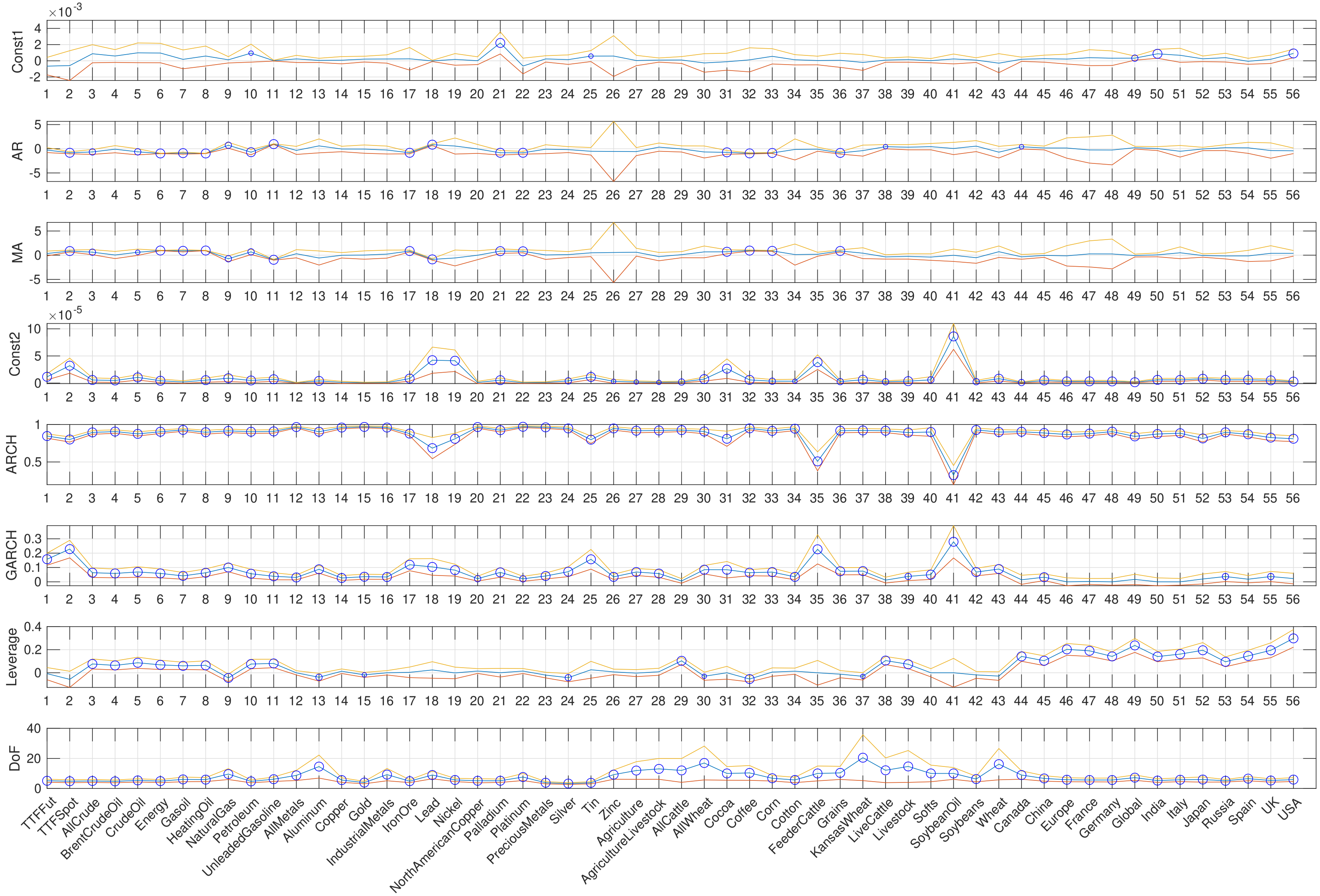
The figure shows plots for the parameter estimates of the ARMA(1,1)-GARCH(1,1) model for all assets. The light blue line shows the coefficient value, the yellow line is the upper 95th bound of the confidence level, the orange line is the lower 95th bound of the confidence level. Large blue circles correspond to p-value $\leq 1.00\%$; medium blue circles correspond to p-value $\in (1.00\%, 5.00\%]$; small blue circles correspond to p-value $\in (5.00\%, 10.00\%]$; Otherwise p-value $> 10.00\%$.

Figure 2: ARMA(1,1)-EGARCH(1,1) parameter estimates



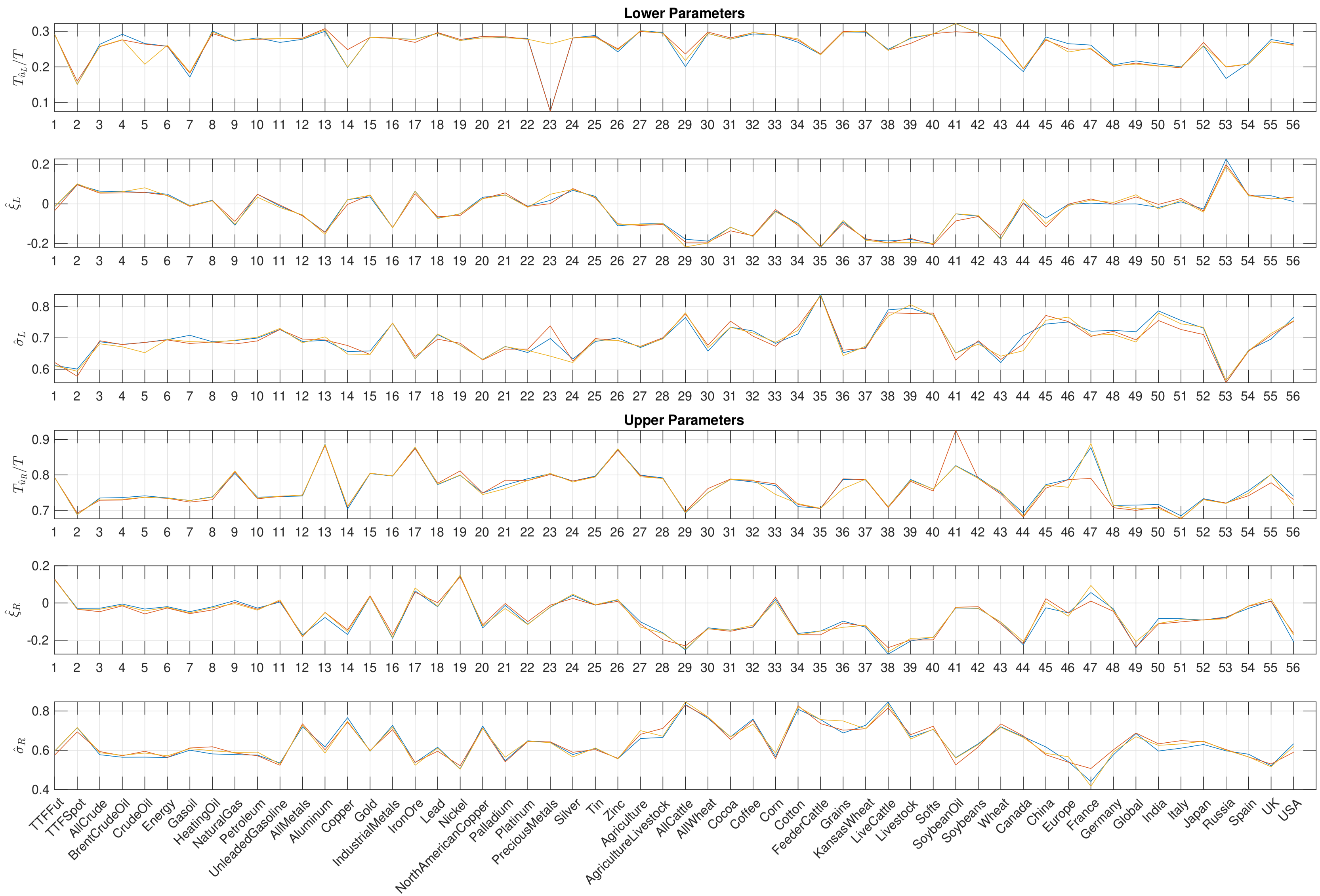
The figure shows plots for the parameter estimates of the ARMA(1,1)-EGARCH(1,1).

Figure 3: ARMA(1,1)-GJR(1,1) parameter estimates



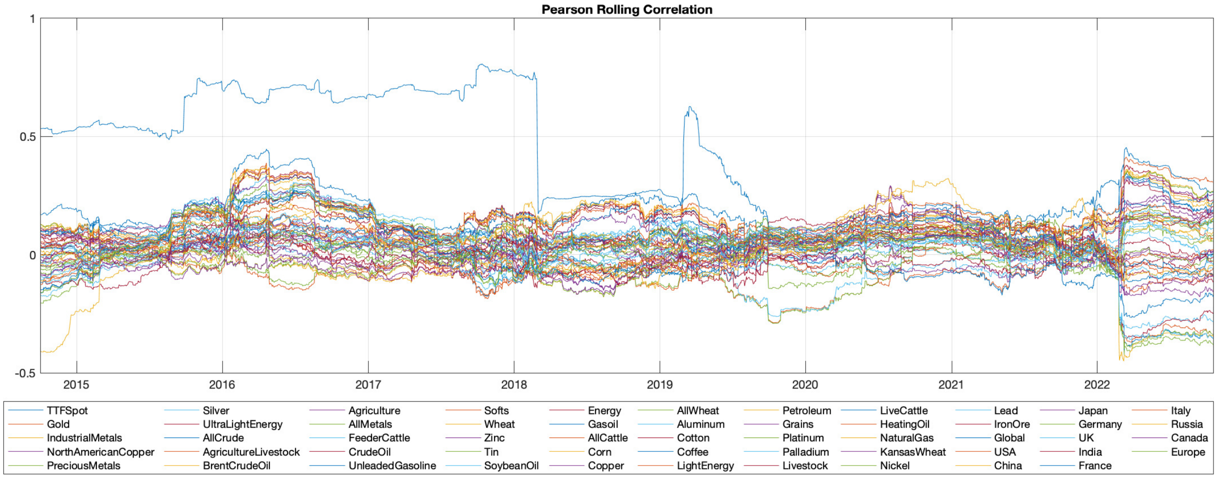
The figure shows plots for the parameter estimates of the ARMA(1,1)-GJR(1,1).

Figure 4: Piece-wise Cumulative Distribution Function, Pareto Tails parameter estimates



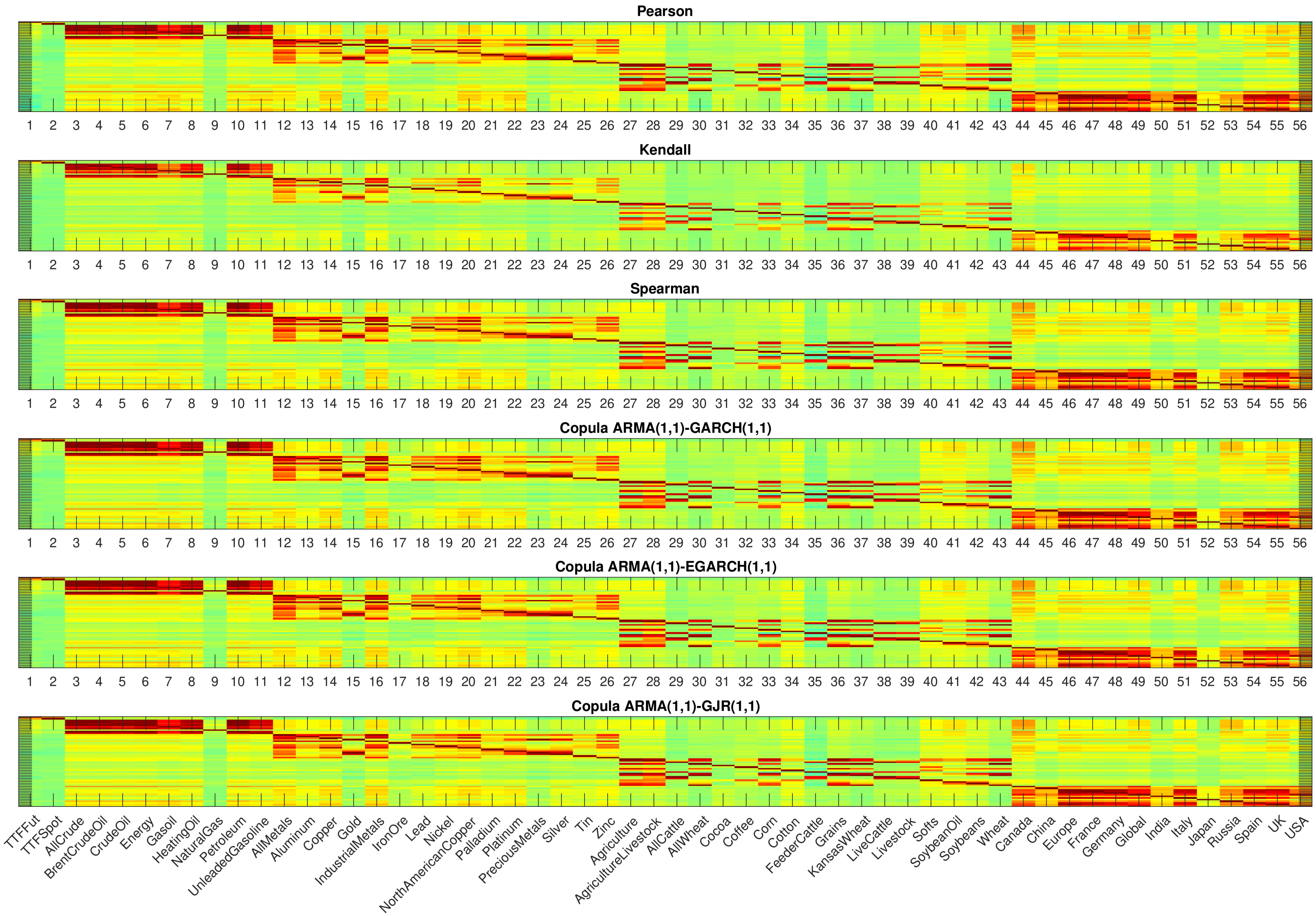
The figure shows plots for the parameter estimates of Piece-wise Cumulative Distribution Function, Pareto Tails parameter estimates. The blue line depicts estimates for ARMA(1,1)-GARCH(1,1) standardized residuals. The red line represents estimates for ARMA(1,1)-EGARCH(1,1) standardized residuals. The yellow line corresponds to the estimates over the ARMA(1,1)-GJR(1,1) standardized residuals.

Figure 5: Rolling Pearson correlations



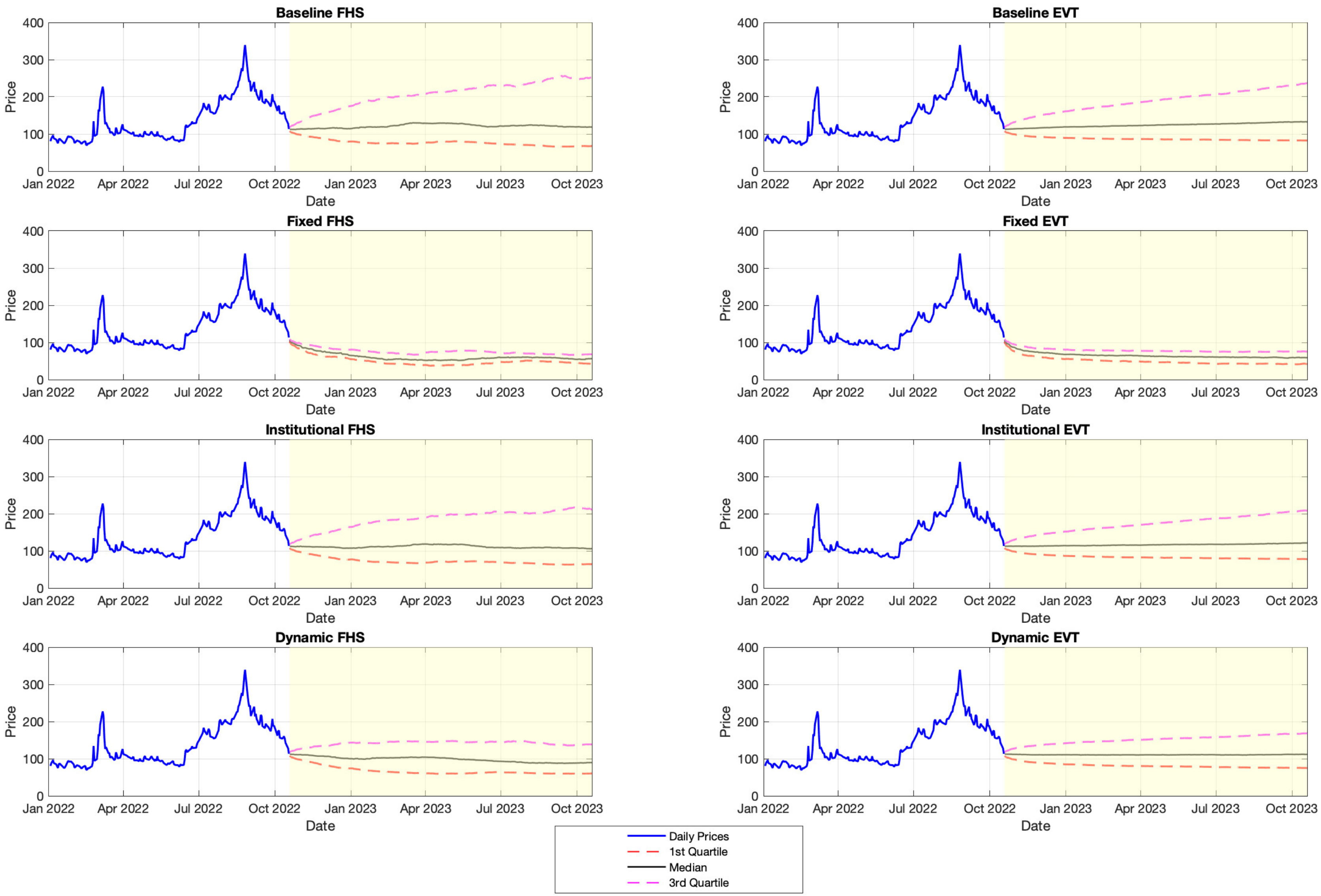
The plot shows rolling Pearson correlation coefficient of *TTFFut* with other commodities and equity indices computed on 250-day rolling windows.

Figure 6: Correlation measures between assets



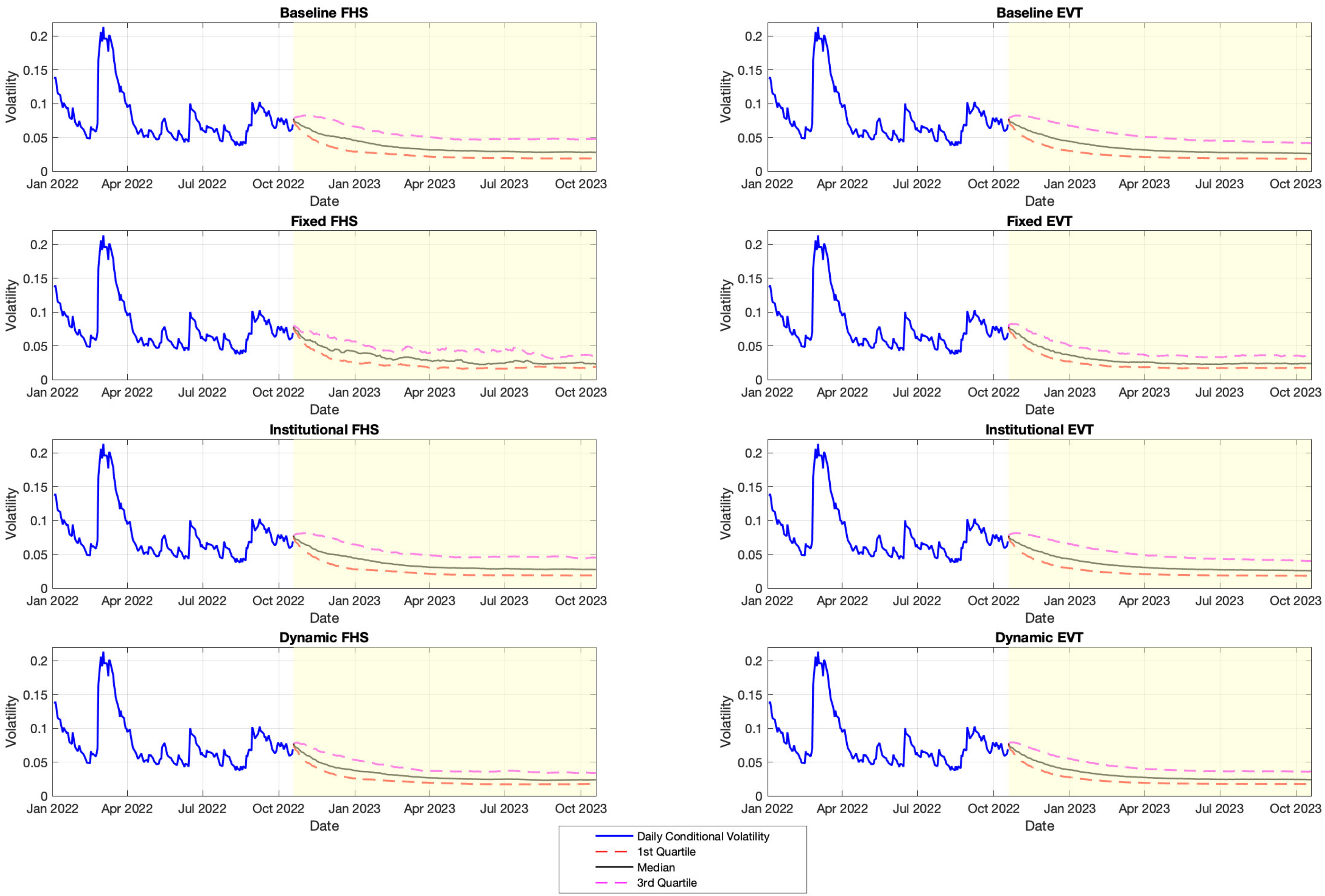
The figure shows plots for correlation between assets using different approaches. The first plot shows the Pearson correlation coefficient. The second plot shows the Kendall correlation coefficient. The third plot shows the Spearman correlation coefficient. The last three plots shows the dependence structure from t-copula based standardized residuals of ARMA(1,1)-GARCH(1,1), ARMA(1,1)-EGARCH(1,1) and ARMA(1,1)-GJR(1,1). A blue value indicates perfect negative correlation. A green correlation indicates a perfect null correlation. A red value indicates perfect positive correlation.

Figure 7: *TTFFut* price forecasts over different scenarios



The plots show *TTFFut* prices forecasts. The blue solid line is the historical daily prices. The yellow area correspond to the forecasting time horizon. The red line is the first quartile. The pink line is the third quartile. The black line is the median. Forecasts from the three conditional models have been averaged.

Figure 8: *TTFFut* volatility forecasts over different scenarios



The plots show forecasts for *TTFFut* daily conditional volatility. The blue solid line is the historical daily conditional volatility (averaged over the three conditional models). The yellow area correspond to the forecasting time horizon. The red line is the first quartile. The pink line is the third quartile. The black line is the median. Forecasts from the three conditional models have been averaged.